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Urban Variation Through Evolutionary Development

Evolutionary Processes in Design and the Impact of Multi-Objective Evolutionary Algorithms Generating Urban Form

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Thesis Submitted for the Degree of Doctor of Philosophy

Graduate School of Architecture at the Architectural Association,
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October 2018

Urban Variation Through Evolutionary Development

Evolutionary Processes in Design and the Impact of Multi-Objective
Evolutionary Algorithms Generating Urban Form

The extent to which the mathematics of nature can serve as a generative model to design variation of urban form is dependent upon an understanding of the impact of natural systems on phenotypic variation across natural species, and in specific, the role that evolutionary developmental biology has on the application of these processes in an urban context. Through a thorough analysis of the intersection between the three primary fields of urban variation, biology and computation; multiple methods, that are both generative and analytic, are developed with the aim of establishing an efficient, effective and robust *modus operandi* for the application of biological evolutionary principles in generating urban variation. Utilising urban blocks and superblocks within multiple urban tissues that differ in location, environment and historical context; the research is developed through a progression of 5 key experiments that advance the methods and tools developed for their application in design problems that range in both scale and complexity; demonstrating the advantages of utilising regulatory mechanisms towards generating varied populations of context-specific morphologies that provide for greater diversity between the phenotypic attributes that characterise the urban superblock.

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7. Showkatbakhsh, M. and Makki, M. (2018) 'Application of Homeostatic Principles within Evolutionary Design Processes: Adaptive Urban Tissues', Journal of Computational Design and Engineering. (Under Review).

Works Related to the Research

Courses

- Evolution: A Course for Educators, Online Course by American Museum of Natural History
Completed in 2018
- Introduction to Genetics and Evolution, Online Course by Duke University. Completed in 2017
- The Changing Arctic, Online Course by Tomsk State University. Completed in 2017

Published Software

- Makki, M. Showkatbakhsh, M. (2018) 'Wallacei: An Analytic Engine for Evolutionary Simulations'
- Makki, M. Showkatbakhsh, M. Song, Y. (2019) 'Wallacei X: An Evolutionary Engine for Evolutionary Simulations'

Conferences and Symposiums Attended

- IEE Congress on Evolutionary Computation (CEC) – Spain, 2017
- The Genetic and Evolutionary Computation Conference (GECCO) – Germany, 2017
- Symposium on Animal Development and its Evolutionary Variation – UK, 2017

Site Visits

- Moscow; Novosibirsk; Irkutsk; Listvyanka; Ulan Ude; Vladivostok – Russia, 2015
- Barcelona – Spain, 2015

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Introduction

The application of biological evolutionary principles as a model for design has gained ground in the last decade. The algorithmic incorporation of evolutionary principles within main stream modelling tools has led to an increase in their application across many disciplines within the field. In recent years, multiple evolutionary engines have been developed in design that utilise the same base algorithmic framework (developed from within computer science), for the purpose of implementing an iterative model that is driven by the primary evolutionary principles of selection and variation, with the aim of addressing design problems through a process of simultaneous optimisation to multiple conflicting criteria.

Although the available evolutionary solvers share similar evolutionary algorithms, they differ from one another through the mode of their implementation within the design tool as well as the methods in which they generate and present the simulation's output. However, their development and use within the field has been predominantly focused on the algorithm itself rather than the stages and sequences required both before and after the algorithm's implementation. In doing so, more is expected from the algorithm (which in its simplest form is a rule based iterative process) and less attention is given to the setup of the components that are fed into the algorithm and the analysis of the data generated by the algorithm. The consequence of which is an inadequate and inefficient implementation of the evolutionary process as an optimisation model in design.

To address this, the research examines the implementation of evolutionary processes in design through a thorough analysis of the intersection between the three primary fields of urban variation, biology and computation; through which multiple methods, that are both generative and analytic, are developed with the aim of establishing an efficient, effective and robust modus operandi for the application of biological evolutionary principles as a problem-solving mechanism within the design field.

1.1. The Urban Argument

In the context of the rapid growth of urbanised population and the effects of climate change and diminishing natural resources, the methodology by which cities are designed in the next 30 years is crucial to the success or failure of sustaining the growing numbers in the population; as proclaimed by the UN, "the 21st century is the century of the city". The conventional method of urban planning implemented in the 20th century, in which the city was designed not unlike a machine, adhering to an idealistic notion of planning a generic city that is applicable regardless of region, climate or topography, commonly resulted in dire impacts on both global and local scales. Despite the centralised models of the sciences, especially biology, weakening and being replaced with bottom-up approaches, city planning continued to develop in the opposite direction; forcing the notion that the city needed an architect, one who knew how to design a city to benefit all who lived within it. However, to conceive the city as a single designed artefact, "denies its natural underlying diversity, complexity and dynamism, as well as time and historical evolution; a denial which ultimately restricts future growth and development" (Farrell, 2013, p.

97). This has triggered a reassessment and revision of traditional urban design methods in order to establish a more sustainable *modus operandi* for urban development. In recent years, this has propagated an in-depth analysis of understanding a city within a biological context, an analogy introduced as early as the late 19th century by Patrick Geddes. In this perspective, developing a city as an organism, through a biological evolutionary model, provides a more substantial and applicable methodology for cities that develop through adaptation rather than optimisation, reflecting traits – already acquired by natural systems – of energy efficiency, environmental response, regeneration and climatic and cultural adaptation.

The world is facing the ever-pressing issue of population growth; the world's population has risen from 2.5 billion in 1950 to 7.6 billion in 2017, and according to the UN, is expected to reach 9.8 billion in 2050 (UN, 2017). On the other hand, the world's urban population has risen from 34% in 1960 (1.02 billion people) to 54% in 2014 (3.78 billion people) (UN, 2018) (figure 1.1.). The UN also predicts that the number of people living in cities is expected to grow to 68% in 2050; this amounts to 6.65 billion people. Such rapid growth in urban population does not only necessitate an increase in the number of cities required to be built in the next 30 years, but also brings to light the increasing demand on the world's already diminishing natural resources required to sustain the anticipated population growth. Therefore, the methodology by which cities are designed in the next 30 years is crucial to the success or failure of the efficient use of natural resources to sustain the growing numbers in the population (figure 1.2.).

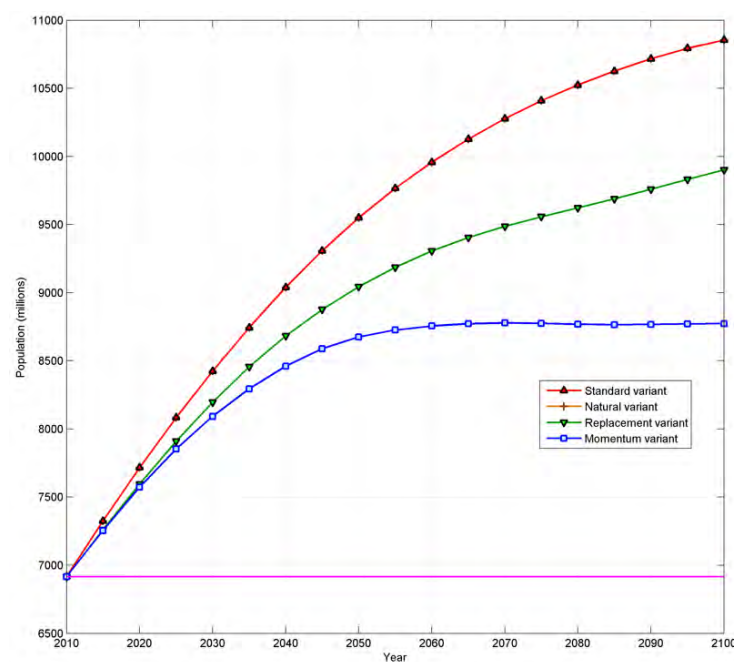


Figure 1.1.
Population Growth: Projected population growth as predicted by the United Nations; it is predicted that the world's population will increase by 3.9 billion people by the year 2100, reaching a total approximate population of 10.9 billion (Andreev et al., 2013).

The increasing greenhouse gas concentrations in the atmosphere, the warming of the oceans, the diminishing amount of ice and snow and the rising sea levels that have been recorded since the 1950s argues that a new, sustainable approach to designing cities is essential for an improved climate. Therefore, the conventional method of urban planning implemented in the 20th century that adheres to the idealistic notion of planning a generic city that is applicable regardless of region, climate or topography, must be revised and reassessed to establish a more sustainable *modus operandi* for developing urban plans.

The modernist approach to cities in the past half-century has been formulated around treating a city as both a system that is independent from its environment and one that is usually in an equilibrium state. This top-down approach to cities reflected a process of planning and management; a master plan was designed in a 2-dimensional format primarily through the distribution of locations and spaces in the form of different zones (industrial, residential, business etc.), followed by establishing the connections between these different locations. The master plan was implemented with the notion that once constructed, the city was perceived to be 'complete' (Batty and Marshall, 2009). However, 'completion' was seldom achieved, as it was a substantially idealistic perception. The factors that dictate the growth rate and development of a city cannot be expressed and implemented through a 2-dimensional representation of location and space distribution. This has been proven in an array of examples that range in scale and timeframe. Two of which are Brasilia and Milton Keynes. The former was designed in the mid-20th century to accommodate a population of 500,000 people, however by the year 2000, the population of Brasilia reached 2 million and has reached close to 2.5 million in 2012 (Banerji, 2012). Milton Keynes on the other hand was designed primarily as a poly-centric plan, through the distribution of different business centres throughout the city; however, the unexpected rapid growth of one business centre during the city's development resulted in the failure of the remaining business centres to compete, thus transforming the city into a mono-centric one (Edwards, 2001).

Such unexpected outcomes are due to the fact that cities are governed by the stakeholders that comprise the city and the efficiency of the networks and flows between these individuals. Thus, rather than perceiving cities as distributions of locations and spaces, with connections as an afterthought, Michael Batty (2013) argues that cities must be analysed as a set of interactions, communications, flows, relations and networks that dictate the locations and spaces within the city. Batty simplifies this by stating, "Location is, in effect, a synthesis of interactions" (Batty, 2013, p. 13). Therefore, rather than approaching cities as machine systems, Batty (2013) contends that a city must be considered as an organism, a system that is ever-evolving, one that is in a perpetual dialogue with its environment, continuously adapting to changes dictated by the individual and group decisions that comprise the city. Brasilia and Milton Keynes exemplify the lack of control over the growth rate and final outcome of a city; cities designed with idealistic goals that could only have been achieved were they independent from their environment.



Figure 1.2.
Population Growth and
Urbanisation (left: Sao
Paulo, right: Johannesburg).
The effects of increasing
populations will be felt by the
poorest demographic (Miller,
2018; Davis, 2011).



The argument against modernist planning emerged within a relatively short period of its inception, in as early as 1942, Jose Luis Sert (1942), states that “In its academic and traditional sense, city planning has become obsolete. In its place must be substituted urban biology”, in which he was likening a city to an organism that is born, expands, disintegrates and dies. However, Sert’s analogy between cities and natural systems was not the first; others, including Arturo Mata (1892), Ebenezer Howard (1898), Patrick Geddes (1915), Ernest Burgess (1925) and Lewis Mumford (1938) have all made a case for interpreting the city as a living being (some more forcefully than others). The early relationships drawn between natural systems and the city have seldom evolved beyond ‘the analogy’, persisting as only metaphorical interpretations within the theoretical discourse of city design; however, the impact of comparing cities to organisms had a more profound effect later on in the 20th century as it laid the groundwork to an alternative approach to city design, in which cities were recognised as emergent systems that develop through bottom-up processes rather than top-down applications. This was evident in the work of Jane Jacobs (1961) and Christopher Alexander (1964), and although their message largely diverged from the heavily controlled and designed processes of city planning of the time, they established a strong correlation between the biological sciences and city development, paving the way for a new model of a city that is approached as an emergent system with inherent properties of diversity and formal variation that have been missing from the modernists approach.

1.2. The Biological Argument

The paradox of the biological model of evolution is in its simplicity. One cannot help but question how such a complex system, one that has generated the diversity between all species on earth in which all species (without exception) are related to one another and descendent from a single common ancestor (figure 1.3.), can be explained through a process that is comprised from two primary steps (Carroll, 2007).

1. Descent with modification; in which variation takes place within the genetic code of an organism from parent to child.
2. Natural Selection; in which the variation within the organism’s genetic code creates phenotypic traits that give the organism an advantage (or disadvantage) for its survival.

So simple in its explanation, that it prompted the biologist Thomas Huxley to state “How extremely stupid not to have thought of that!” (Huxley, 1900, p. 105) upon reading Charles Darwin’s *On the Origin of Species* (1859), in which he provides an explanation for the mechanisms behind the evolutionary process. Although Darwin’s theory was challenged by many in the field, it was through the technological advancements of the 20th century that created the scientific evidence required to synthesise his theories and gain acceptance amongst the majority of scientists in the field. However, Darwin’s theories coupled with the associated research conducted since the publication of his book has extended evolutionary thought well beyond the field of biology,

establishing itself as a unifying discipline (Smocovitis, 2016) that has expanded beyond the confines of its domain and into other disciplines such as geology, psychology, literature, medicine, music, economics, computation and design (van Wyhe, 2016; Corne and Bentley, 2001).

Extracting the biological principles of variation and selection as the driving mechanisms for a problem-solving model has proven to be influential in the application of an evolutionary process across multiple disciplines; to appreciate its significance and its cross disciplinary properties, one must first explain the evolutionary model itself; Organisms change through an iterative process of incremental variation and selection in response to the stresses exerted on the organism by its environment. By doing so, the environment directs the population towards one that retains the organisms that are better adapted to the environmental conditions and discards the organisms that are not. Most importantly, the evolution of these fitter organisms takes place without the need for a driving mechanism that is external/independent to the system. In this context, and to abstract it even further, the *problem* is the environment, and the *solutions* are the organisms that have evolved to be better suited to the environment. This provides a framework that can be adapted in multiple disciplines as a model to find solutions to complex problems, especially when the problem is associated with multiple solutions that are different from one another. This framework can be further synthesised through the following statement:

The evolutionary process is a robust model for generating solutions (organisms) that are optimised (adapted) to a problem (environment) without forces external to the system.

The above interpretation of an evolutionary process is inherently emergent, it is a model that generates variation through a bottom up process that is contingent on local interactions (rules) between the different components of the system, which in turn generates solutions that are both diverse and well adapted to their environmental conditions. Within the domain of design, and in specific, urban design, the evolutionary model presents itself as a powerful alternative approach to the top-down processes associated with the 'planned' cities of the 20th century which assumed that the city's bottom-up organisation can be manufactured and managed through idealistic and predictive planning processes (Batty and Marshall, 2012).

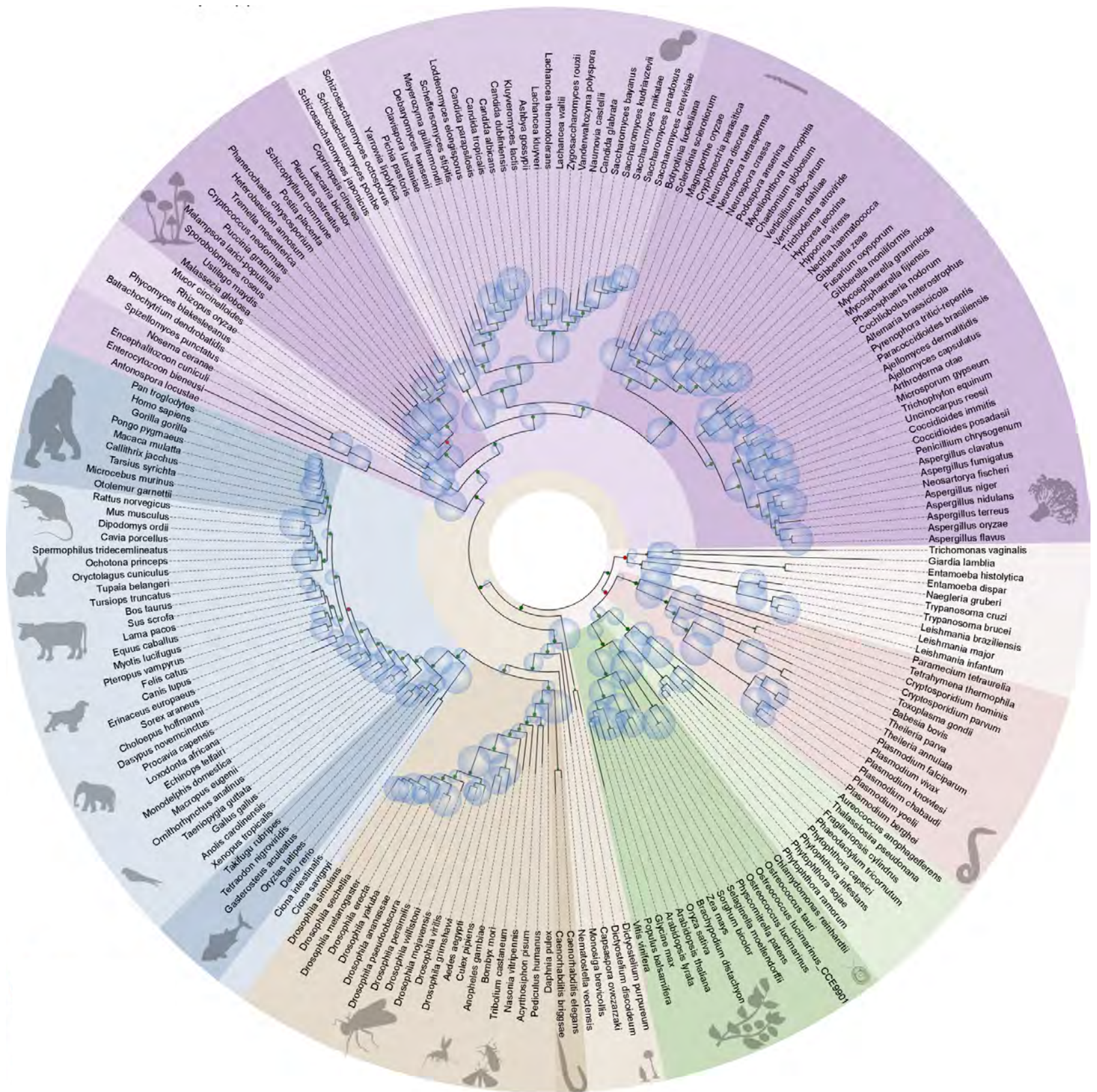


Figure 1.3.
Tree of Life: All species on earth
are related to one another and
a descendent from a single
common ancestor (Huerta-
Cepas et al., 2014).

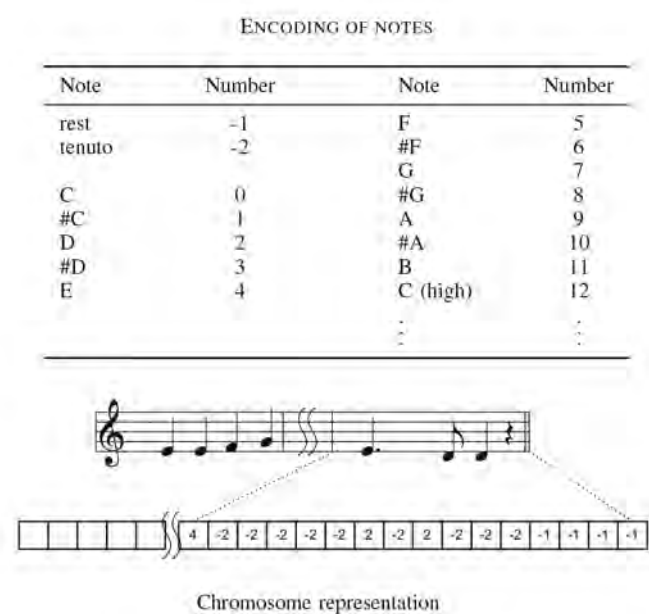
In this context, understanding the relationship between a biological natural system to its environment is crucial to translate the factors that govern the evolution of natural systems towards city growth and development. To understand the ability of creating order with functionality, evolution serves as an optimal model. Contrary to the conventional planning methods of the 20th century, natural systems do not evolve towards a predefined goal, as this deems the system to be one that is self-contained; therefore, rather than optimisation, natural systems evolve and develop through adaptation. Emphasis must be placed on the term adaptation as it greatly signifies the fact that the evolution of a natural system is completely dependent on the ability of the system to successfully transform itself and adapt to its environment. Ernst Mayr (2002) emphasised the significance of a natural system to adapt to its environment by attributing it as a relationship of “perfection”, although the use of this term may be construed as teleological, Mayr clarifies that by perfection he means “the seeming adaptodness of each structure, activity and behaviour of every organism to its inanimate and living environment” (Mayr, 2002, p. 163). The adaptation between a system and its environment is one of the corner stones of a biological model of evolution, as it results in an efficient exchange of resources between the two; thus, the significance of a city’s morphology to adapt to changes in its climate, ecology, resources and population is crucial in developing the sustainable longevity of a city; further signifying the need for the shift from understanding a city as a machine to that of an organism.

1.3. The Computational Argument

The utilisation of evolutionary principles in computation dates back to the mid-20th century; the earliest applications of an evolutionary process as a problem-solving model was evident through the work of Fraser (1957) and Friedberg (1958). Although the field has expanded and developed exponentially throughout the remainder of the century to today, with its applications evident across multiple disciplines, the significance of the computational applications of evolutionary principles is heavily contingent on the understanding of algorithmic modelling and the relevance of iterative processes, through this, the argument for the computational application of an evolutionary model in design is strengthened.

Detailing the algorithmic applications of evolutionary principles must first be preceded with the historical significance of the algorithm. The term *algorithm* is a Latin derivative (Algoritmi) of the Persian mathematician’s name, *Mohammad ibn Musa al-Khwarizmi*, considered as one of the founders of algebra (The word algebra itself is derived from the Arabic word *Al-Jabr* (which means *to reunite disassembled parts*), which was used by the 9th century mathematician in his book *Al-Kitāb Al-Mukhtaṣar Fī Hisāb Al-Jabr Wa’l-muqābala* (*The Compendious Book on Calculation by Completion and Balancing*) (Mehri, 2017)). In its purest form, the algorithm is a “set of step by step instructions, to be carried out quite mechanically, so as to achieve some desired result” (Chabert, 2012, p. 1); in this context, *mechanically* does not mean manually, it is defined as a process that successively iterates through a clearly defined and finite number of steps that starts with an *initial state* and terminates in an *end state*. This has formulated the basis for all algorithmic processes throughout the past millennium. However, it was through the advent of computation that the algorithmic process was used to solve problems in disciplines other than mathematics.

It is generally agreed amongst researchers and scientists that the first computer programmer was the English mathematician, Ada Lovelace, in which her most significant contribution to the field is what has been considered to be the first algorithm ever written to be run by a machine. Moreover, her notes, which accompanied her translation of Charles Babbage’s *Analytic Engine* (Babbage and Lovelace, 1843) claimed that the analytic engine can be used for more than just calculating equations; it has the ability to calculate any problem that can be represented numerically, in which she used musical composition as an example (Palermo, 2015); her intent was to shift from a *calculation* mindset into a *computational* one (In the most recent conference on evolutionary computation (CEC 2017), three research papers have been presented in which an algorithm was used to compose an original piece of music (Liu and Ting, 2017; Lopes et al., 2017; Vega, 2017) (figure 1.4.). Ada Lovelace’s short but highly influential research lays the foundation for the computational and digital age of modern day; and although others have followed in Ada Lovelace’s footsteps, having an equal (if not greater) impact on modern day algorithmic thinking (through the work of seminal figures such as Alan Turing and John von Neumann), it was Lovelace’s initial concepts of a “general-purpose machine, one that could not only perform a pre-set task but could be programmed and reprogrammed to do a limitless and changeable array of tasks. In other words...the modern computer” (Isaacson, 2014, p. 67), that has been embodied throughout the 20th century.



The computational translation of the algorithmic process allowed researchers to investigate fields of study that were previously too difficult or complex to simulate. More importantly, it created an opportunity for cross collaboration between the disciplines. This is exemplified through algorithmic simulation of an evolutionary process, in which the different disciplines of

Figure 1.4.
Algorithmic composition:
Music created through the use
of evolutionary computation
by encoding notes into
numerical representations (Liu
and Ting, 2017).

biology, computer science and engineering all had a stake in the algorithmic translation of an evolutionary model. Where biologists aimed to better understand evolutionary systems through their algorithmic simulation, computer scientists and engineers were driven by the ambition of harnessing the power of evolutionary processes as a model for solving complex problems. Through the initial success of this cross disciplinary approach to the algorithmic modelling of evolutionary principles, their implementation has continued to expand through other disciplines. This has been made possible due to the adaptive nature of the algorithmic model; in which each discipline is able to specify different methods of calculation and evaluation yet remain within the confines of the evolutionary algorithm (figure 1.3.).

The above highlights the profound impact of mathematical algorithmic processes and their consequent computational translation in the development of countless fields. The cross-disciplinary nature of the algorithmic process is predominantly a result of its simplicity; the iterative process in which a set of rules is applied locally between the components of the system in order to define a more complex whole is a robust model to address problems that cannot be solved through brute force, top-down approaches. Moreover, and specifically within the field of urban design, the application of computational algorithmic methods that incorporate evolutionary strategies is essential to understand a system that is emergent in behaviour and inherently complex; a system that exhibits long term change through successive iterations of local interactions between the different entities that comprise it.

Diagram for the computation by the Engine of the Numbers of Bernoulli. See Note G. (page 722 *et seq.*)

Number of Operation.	Nature of Operation.	Variables acted upon.	Variables receiving results.	Indication of change in the value on any Variable.	Statement of Results.	Data.										Working Variables.										Result Variables.			
						$1V_1$	$1V_2$	$1V_3$	$1V_4$	$1V_5$	$1V_6$	$1V_7$	$1V_8$	$1V_9$	$1V_{10}$	$1V_{11}$	$1V_{12}$	$1V_{13}$	$1V_{14}$	$1V_{15}$	$1V_{16}$	$1V_{17}$	$1V_{18}$	$1V_{19}$	$1V_{20}$	$1V_{21}$	$1V_{22}$	$1V_{23}$	
						1	2	n																					
1	\times	$1V_2 \times 1V_3$	$1V_6$	$1V_8$	$1V_8 = 1V_2 \times 1V_3$...	2	n	2n	2n	2n	
2	$-$	$1V_4 - 1V_1$	$1V_4$	$1V_4$	$1V_4 = 1V_4 - 1V_1$...	1	
3	$+$	$1V_5 + 1V_1$	$1V_5$	$1V_5$	$1V_5 = 1V_5 + 1V_1$...	1	
4	$+$	$1V_6 + 1V_4$	$1V_6$	$1V_6$	$1V_6 = 1V_6 + 1V_4$	
5	$+$	$1V_{11} + 1V_2$	$1V_{11}$	$1V_{11}$	$1V_{11} = 1V_{11} + 1V_2$...	2	
6	$-$	$1V_{13} - 1V_{11}$	$1V_{13}$	$1V_{13}$	$1V_{13} = 1V_{13} - 1V_{11}$	
7	$-$	$1V_5 - 1V_1$	$1V_5$	$1V_5$	$1V_5 = 1V_5 - 1V_1$...	1	...	n	
8	$+$	$1V_2 + 0V_2$	$1V_2$	$1V_2$	$1V_2 = 1V_2 + 0V_2$...	2	
9	$+$	$1V_6 + 1V_2$	$1V_6$	$1V_6$	$1V_6 = 1V_6 + 1V_2$	
10	\times	$1V_{11} \times 1V_{11}$	$1V_{11}$	$1V_{11}$	$1V_{11} = 1V_{11} \times 1V_{11}$	
11	$+$	$1V_{12} + 1V_{11}$	$1V_{12}$	$1V_{12}$	$1V_{12} = 1V_{12} + 1V_{11}$	
12	$-$	$1V_{10} - 1V_1$	$1V_{10}$	$1V_{10}$	$1V_{10} = 1V_{10} - 1V_1$...	1	
13	$-$	$1V_6 - 1V_1$	$1V_6$	$1V_6$	$1V_6 = 1V_6 - 1V_1$...	1	
14	$+$	$1V_1 + 1V_2$	$1V_2$	$1V_2$	$1V_2 = 1V_2 + 1V_1$...	1	
15	$+$	$1V_6 + 1V_2$	$1V_6$	$1V_6$	$1V_6 = 1V_6 + 1V_2$	
16	\times	$1V_6 \times 1V_{11}$	$1V_{11}$	$1V_{11}$	$1V_{11} = 1V_{11} \times 1V_6$	
17	$-$	$1V_6 - 1V_1$	$1V_6$	$1V_6$	$1V_6 = 1V_6 - 1V_1$...	1	
18	$+$	$1V_1 + 1V_2$	$1V_2$	$1V_2$	$1V_2 = 1V_2 + 1V_1$...	1	
19	$+$	$1V_6 + 1V_2$	$1V_6$	$1V_6$	$1V_6 = 1V_6 + 1V_2$	
20	\times	$1V_6 \times 1V_{11}$	$1V_{11}$	$1V_{11}$	$1V_{11} = 1V_{11} \times 1V_6$	
21	\times	$1V_{12} \times 1V_{11}$	$1V_{12}$	$1V_{12}$	$1V_{12} = 1V_{12} \times 1V_{11}$	
22	$+$	$1V_{12} + 1V_{11}$	$1V_{12}$	$1V_{12}$	$1V_{12} = 1V_{12} + 1V_{11}$	
23	$-$	$1V_{10} - 1V_1$	$1V_{10}$	$1V_{10}$	$1V_{10} = 1V_{10} - 1V_1$...	1	
Here follows a repetition of Operations thirteen to twenty-three.																													
24	$+$	$1V_{12} + 1V_{11}$	$1V_{12}$	$1V_{12}$	$1V_{12} = 1V_{12} + 1V_{11}$	
25	$+$	$1V_1 + 1V_2$	$1V_2$	$1V_2$	$1V_2 = 1V_2 + 1V_1$...	1	...	n+1	

Figure 1.5.
The first Computer Algorithm:
Written by Ada Lovelace
and published in 1843 in
the 'Sketch of the Analytical
Engine by Charles Babbage,
Esq' (Haines, 2015).

1.4. Research Focus

The research seeks to establish a correlation between the factors that govern the evolution of species in nature with the factors that regulate the development of cities in multiple geographic and climatic locations. The coupling of these two fields is approached through the algorithmic application of evolutionary principles driven by a biological model that incorporates gene regulation and regulatory sequences which have been developed within the biological subfield of evolutionary development. Through a thorough analysis of the historical implications of both planned cities and evolved cities and the impact of environmental stresses on their urban fabric, the research aims to develop urban tissues that share the merits of both urban approaches by means of applying a 'directed evolutionary model', one that is governed through continuous revisions applied to the variables driving the system. In doing so, the research establishes a generative approach that develops urban tissues, comprised from morphological variation of their blocks and superblocks, that have been optimised through multiple iterations of local interactions with the environment.

To facilitate this, the research pursues the knowledge and skills required through a comprehensive analysis of the biological processes of evolutionary thought in addition to gene regulatory mechanisms; a subfield of biological evolution that is pivotal in explaining the evolution of morphological variation between species and thus is critical for the effective and plausible application of an evolutionary model within computation. Furthermore, a thorough review of the current forms of the application of biological principles within evolutionary computation (evolutionary algorithms, genetic algorithms, multi-objective evolutionary algorithms, etc.) is critical to establish the necessary foundation that facilitates the integration of the most recent advances in biological evolution to their algorithmic application within a computational environment.

Additionally, the research addresses the current applications of evolutionary algorithms in design, in which the lack of an analytical feedback mechanism that assists users in running efficient and well developed evolutionary simulations has almost defied the purpose of the application of an evolutionary process. As such, the research aims to address the significance of numeric data – and its analysis – in the computational process through developing multiple tools that help in creating an efficient workflow for the translation of a biological system as a problem-solving model.

1.4.1. Research Questions

The research is focused on the analysis of two primary domains, the development of urban variation through biological processes (urban) and the computational application of the biological processes in design (computation). Therefore, the research questions are categorised through these two areas of study:

Urban and Computation

- Can the science of evolutionary developmental biology be implemented as a computational model to generate diverse and optimised morphological variation of urban blocks and superblocks?

Urban

- Can a generative evolutionary model be applied to generate urban variation for evolving cities and planned cities located in two extreme climates?
- Can an evolutionary model, operating across a range of scales, enable the development of urban superblocks that are evolved in response to stresses from their environment?

Computation

- Can the data outputted by the evolutionary simulation be used as a feedback mechanism to reformulate the design problem in order to construct a more efficient simulation?
- Can the algorithmic application of a biological evolutionary process dynamically control variation within the population without external drivers?

1.5. Research Significance and Contribution

The aim of this research is to provide contribution to two primary fields of study. Firstly within urban design; the modernists approach to urban development is one that has been predominantly top-down with idealistic notions that emphasised the *generic*, usually resulting in an undesirable impact on the urban fabric. Recently however, researchers such as Bill Hillier and Julienne Hanson, in their book 'The Social Logic of Space' (1984) and Michael Batty, in his book 'The New Science of Cities' (2013) have utilised different tools in the understanding of cities through mathematics and complexity sciences, yet the mode of their application has remained primarily analytical rather than generative. Comparative analyses of city planning and biological evolution have also been debated by different researchers throughout the 20th century. Patrick Geddes in his book 'Cities in Evolution' (1915) touched upon this relationship, however the main premise of his book focused more about "civics' and 'city design' (rather) than a systematic application of evolutionary theory to understanding urban change" (Marshall, 2008, p. 13). Although more

recent attempts have applied evolutionary models in a systematic sense in cities and urbanism in general, such as the one put forth by Stephen Marshall in his book *Cities, Design and Evolution* (2008), it is still approached from a generalised and analytical perspective, where the author deems it unnecessary to go into detailed correlations between biological evolution and city planning. Thus, the research presented aims to build upon the findings and analysis of previous researchers through developing a *generative* approach that couples evolutionary processes to urban development, one that signifies variation between urban blocks and superblocks as opposed to their repetition.

The second field of contribution is within computation and its application in design, more precisely, pertaining to the application of evolutionary computation for urban variation. This is comprised from two parts:

Computational models of problem solving and ‘optimisation’ derived from evolutionary theory have been developed extensively since the mid-20th century onwards. Although this form of computation remains widely implemented across a range of different fields, the evolutionary principles driving these computational models remain centred around Darwinian principles synthesised in the early part of the 20th century and have yet to conform with advancements in evolutionary science – especially those discovered in the fields of developmental biology and genetics – that date as far back as the 1980s. Although there have been some attempts to bridge this gap by different researchers, they are few and far apart that their results are localised to their own research domain, which is predominantly centred in the computer sciences, thus establishing no dominant presence in design.

Secondly, the application of evolutionary processes in design has been so far presented to users as a *black box*. This does not imply that users of the evolutionary model must have profound knowledge of the inner workings of the algorithmic setup, however, treating the algorithm as a black box creates a false sense of trust that the algorithm will *always* output desirable results. This is seldom the case, as unlike in the computer sciences, the problem presented to the algorithm in design cannot be easily translated to arithmetic functions without a well thought and efficiently developed design problem. Therefore, if provided with a poorly formulated problem, the algorithm’s output will be an inefficient one. Due to this, most current applications of evolutionary algorithms in design do not take full advantage of the evolutionary model and so are working with a *limited* toolset, one which they plug in to and out of without questioning or modifying their original input, which comprises 90% of their evolutionary simulation. To address this issue, the numeric analysis of the outputted data is critical for *debugging the problem* (not the algorithm), and so developing an analytical workflow that feeds back into the design problem with the intention of making it more streamlined proves to be a profoundly important tool for the efficient and correct application of evolutionary processes in design.

Through this, the thesis brings significant attention the processes at either end of the evolutionary process. The frontend of the evolutionary simulation encapsulates how the design problem is formulated; i.e. how the genes (variables), fitness functions (objectives) and body parts (morphological attributes of the phenotype) interact with and influence one another, and whether the relationship between these three core attributes of the design problem are interacting with one another so as to ensure (or to a lesser degree increase the chances of) the optimization algorithm of generating solutions that are well adapted and fit to the objectives of the design problem. On the opposite end of the spectrum, the backend of the evolutionary simulation addresses the methods by which solutions are analysed and selected. i.e. what are the analytic tools and methods being employed to ensure that a complete and comprehensive understanding of the simulation's output is achieved; this is to serve two purposes, the first is to assist in filtering through a significant amount of data (in the form of generated solutions) and select the solutions that are most suitable in addressing the design problem, and second is how well can the analysis of the simulation's output inform inconsistencies or revisions that are required in the frontend of the simulation.

In short, the front and backend are not independent from one another nor are they without influence on each other; a well formulated frontend holds significant weight in ensuring the backend is successful, and a thorough backend ensures the design problem in the frontend is well formulated and effective.

1.6. Research Methodology

The research methodology is an evolving set of experiments that are founded on systematic observations and measurements of urban forms and patterns, the formulation of computational procedures from those observations that are tested by experiment, the subsequent modification of the input and ambition of each experiment based on analysis of the outcome, and further experimentation until the research questions are answered in the measured results of the experiment.

The broad context of the research is Design Research, and the understanding that Design Research is a unique class of inquiry that includes a combination from the larger set of principles of form and behaviour, integrated knowledge from the natural or cultural sciences, a specified degree of mutability that is manifested as a relational model capable of adaptation to differing circumstances or environments, tested principles of implementation, and an expository design of a population of mathematically defined and precise urban configurations that exhibit morphological coherence with a high degree of variation with defined behaviours that have been used to test and evaluate the Design Research.

In his book, 'Sciences of the Artificial', Herbert Simon argues that internal operations and the interactions with the external environment of an artificial system require a design process driven

by the natural sciences, highlighting the necessity of repetitive computational processes that involve analysis, successive propositions and simulations (Simon, 1996, 1969).

Design Research, as an academic discipline with its own body of scholarship and knowledge, is defined by Leonard Archer – a seminal figure in the design research field and founder of the first academic design research post graduate program at the RCA in London (Boyd Davis and Gristwood, 2016) – as a “systematic inquiry whose goal is knowledge of, or in, the embodiment of configuration, composition, structure, purpose, value, and meaning in man-made things and systems” (Archer, 1981, p. 31). Archer’s formulation of design research led to several authors putting forward variations of his definition, primarily by Nigel Cross (Cross, 1982, 1999), and has played a significant role in his influence on design research today (Davis and Reeve, 2016).

As stated in Section 1.5., the research contributes to two fields, firstly within urban design, and secondly in the application of evolutionary processes for generating variation of urban form. In the former, the research examines the significance of variation of urban form and the role it plays in increasing the robustness of urban tissues to address environmental stresses, and the relationship and applicability of similar systems in the natural world, specifically with regards to genetic variation and the significance of how this variation (on both local and global scales – i.e. at the scale of both the individual and the population) affects phenotypic diversity (Section 2.3.3). While in the latter, the thesis examines the methods associated with the application of evolutionary principles in design and the necessity for understanding how the formulation of the simulation’s parameters (and specifically the relationship of these parameters to one another) impacts both the efficiency of the evolutionary simulation as well as deepens the knowledge gained on how well the designed ‘environment’ is formulated; the data and tools necessary to analyse an exponential amount of numeric information and to ensure that the variation among the population is not abstracted so that it is represented by a single ‘average’ individual.

In the general domain of analysing a city, and in the context of applying the scientific method in formulating the ambitions, objectives and analyses of the developed experiments; a step by step, generative and iterative approach to understanding the significance of urban variation and its impact on robustness of urban form is highlighted by addressing the continued use of the ‘generic block’ as a response to an exponentially growing population regardless of region or climate, and the necessity to impose variation of urban form not only with regards to different geographic locations, but also within a single urban tissue. Although there have been attempts by several researchers to highlight the significance of incorporating the scientific method and approach to urban analysis and development (Herthogs et al., 2019; Louf and Barthelemy, 2014; Batty, 2005, 2013; Weinstock, 2010; Hillier and Hanson, 1984), the generic city continues to dominate the urban landscape. In this context, the thesis highlights the significance of numerically precise methods to both analyse and generate urban configurations that have a high and controllable degree of variation. Even though references to the city in the urban science domain are common, they rarely take into account the mathematics of nature despite the domain’s long history of mathematical analysis.

This is highlighted when analysing the difference between Phillip Steadman's original and revised editions of *Evolution of Designs: Biological Analogy in Architecture and the Applied Arts* (1979, 2008). Where in the original edition, the terms evolution, morphology, metabolism, etc., were primarily contextualised as metaphors in design; the revised edition includes an afterward that discusses a 'biomorphic' architecture driven by computational methods that include the 'genetic algorithm'. The shift of focus from the end-product in favour of the process that will generate the end-product, i.e. from morphology to morphogenesis, puts forward the argument of the significance of a population-based approach, informed by varied sets of designs, as opposed to a single unique solution.

Therefore, the extent to which the mathematics of nature can be used as a generative model to design variation of urban form is dependent upon an understanding of the impact of natural systems on phenotypic variation across natural species (Section 2.3.4), and in specific, the role that evolutionary developmental biology has on the application of these processes in an urban context; as it allows for a direct and reciprocal relationship between morphological attributes and the parameters that control these attributes. Through this, the significance between the urban block (and relationship between the different blocks within a superblock) as a unit of measure and the impact of its direct environmental context on its morphological development is brought to the forefront. More importantly, this forms the foundation for the significance of numeric data; highlighting the necessity for the logical, reasoned and methodical development and application of the natural system in formulating the computational model and experiment setup; thus allowing for an understanding of variation in both its morphology and performance.

In this context, the research draws significant knowledge from the biological and computational sciences towards developing multiple design experiments formulated towards addressing the research questions stated in previous sections. In doing so, the theoretical background contextualises the developed computational models for their efficient application in developing multiple design tissues across different geographic and climatic locations.

Background and Context:

The research examines the intersection between 3 primary disciplines, *biology, computation and urban design*. Within biology, two sub-domains are extensively researched, *Darwinian Evolution* and *Evolutionary Development*. The former lays the foundation for the evolutionary principles that will be used as the primary drivers for the developed computational model, while the latter directs the computational model towards greater efficiency in creating morphological variation through the use of a limited (and well regulated) tool set. Although both disciplines are critical for the development of the research, the computational application of Darwinian evolution has been established within the field more widely when compared to the computational application of evolutionary development. Therefore, research into the role of genetics and embryological development (primarily through an in-depth analysis of genetic mechanisms regulating the *body plan*) on generating morphological variation within a single generation and throughout

the population, in addition to the significance of these developmental mechanisms for the environmental adaptation of natural organisms, is key to the successful incorporation of evolutionary developmental principles to the already established Darwinian driven method of evolutionary computation.

In computation, an analysis of the historical development of the field provides the knowledge and background necessary for the successful application and modification of well established (and very successful) evolutionary algorithms. However, the conducted analysis and research extends beyond that of only the theoretical, as it is vital to develop a clear understanding of the development and evolution of different algorithmic functions, and how their development has been driven through the demands of the *user*. For example, to fully comprehend the computational and mathematical driving mechanisms behind multi objective evolutionary algorithms, a thorough analysis must first be carried out on their development from single objective optimisation algorithms and highlight why the former's emergence was in response to the latter's shortcomings. More importantly, and due to the recent surge of evolutionary solvers within design software, it is important to highlight the necessity of using evolutionary engines in design through an in-depth understanding of how they function and address current issues and trends in their application, which have hindered their successful integration within the architectural field.

Thirdly, addressing current issues in urban development through clearly differentiating between *evolved cities* and *planned cities* (or as Christopher Alexander called them, *natural cities* and *artificial cities* (Alexander, 1964)), and the effects of changing climatic conditions and exponential population growth on city development throughout the 20th and 21st centuries. Through this analysis, correlations will be drawn between the field of evolutionary biology and urban design, and the historical significance between the two domains, through highlighting previous attempts to use the former as an alternative approach to develop the latter. Additionally, the research will highlight the significance of the *superblock* as a design unit through an analysis of its development in different time periods and geographic locations. Moreover, the computational advantage of coupling the biological and urban domains will be made clear through highlighting the benefits of using computation as both a modelling tool *and* a generative one. By doing so, the computational application of biological principles for urban variation of blocks and superblocks (and design in general) will highlight existing trends in their application and make clear in what direction they must be developed.

Computational Model:

Multiple computational models are developed, each with the objective of addressing a specific part of the research. Although they are approached differently, the three models are interrelated, and their global application is for the development of the urban fabric. The computational models are divided into three main categories:

Firstly, generating morphological variation within the urban tissue. The developed model utilises the knowledge gained from the biological research into the principles of Darwinian evolution and evolutionary development, and the computational translation of the latter within the established algorithmic framework of the former. The *body plan* is the primary driving mechanism that aims to generate morphological variation within the population through the regulation of different genes to specific parts of the morphology. By doing so, the algorithm will have the necessary toolset to direct the population towards optimising for morphological traits that are better adapted to the environmental stresses acting on the population.

Secondly, computational analysis of the outputted data for its use as a feedback mechanism to debug the design problem. The successful algorithmic application of a biological model as a generative design tool is contingent on how well the design problem is set up; however, the method in which the user can evaluate the design problem is by running it through the evolutionary algorithm. This creates a paradox that is rarely addressed in design. The application of evolutionary strategies in the design field has wrongly assumed that the generated solutions are *always* optimised, and if they are not, the user will automatically *blame* the algorithm. However, as mentioned in previous sections, the algorithm simply runs through steps that are predefined by the user; therefore, if the output is nonsensical, (and the user is confident that the steps in the algorithm are correct), then the problem lies with the input. To address this, a streamlined model is developed that analyses the numeric data outputted from the simulation and highlights inconsistencies by running a comparative analysis on the entire population, thus providing the user with clear guidance on how to modify and better the design problem. More importantly, the proposed model shifts away from the visual analysis of generated solutions towards one that prioritises the analysis of the genotype rather than the phenotype.

Lastly, controlling variation dynamically within the evolutionary simulation. Variation within the population is key, more importantly, one of the greatest challenges of most algorithmic applications of evolutionary strategies is maintaining an adequate amount of variation within the population yet simultaneously optimising towards a group of *fit* solutions. This is described as the challenge of *exploration* (variation within the population) *vs exploitation* (convergence of the population towards a group of fit solutions). In design (and specifically in the urban environment), control over how much variation generated is key. More importantly, controlling the variation *dynamically* as the algorithm is generating solutions is vital for the user to direct the simulation away from local optima (premature convergence) and towards global optima. Therefore, the developed model addresses this by incorporating a population-based measure as a fitness objective to drive the simulation to either increased variation or increased convergence. This will be referred to as the *population-based fitness criteria*.

Design Experiments:

The methods and tools developed (driven by the research of the three domains) are applied in a progression of design experiments each with the intent of building on the successes of the

preceding experiment and further advancing the methods developed for their applications in the consequent experiment (figure 1.6.).

The first experiments (experiments 1A and 1B) examine methods for incorporating regulatory mechanisms within the design problem and assessing their impact within two distinct frameworks. The first examines the developed model's application within a single objective optimisation problem, while the second conducts the same experiment with the same parameters in a multi-objective optimisation problem. Experiments 1A and 1B evolve a population size of 500 solutions and utilise the Cerda Eixample urban block to generate a 16-block superblock as the primitive phenotype used in the evolutionary simulation.

Experiment 2 builds on the methods developed and reformulates the design problem in order to expand the population size outputted by the simulation, in doing so, the impact of statistical analysis on the simulation's output will be studied and the different methods in which this can be conducted to better understand emergent patterns that may have developed throughout the simulation run. Similar to experiment 1, the primitive phenotype is Barcelona's Eixample block; however, the population size in experiment 2 is significantly expanded in which it is comprised from 10,000 solutions (100 generations of 100 solutions each).

Experiments 3 and 4 apply and expand on the methods developed in experiments 1 and 2 through their application for generating urban variation of blocks and superblocks within two urban tissues located in opposing extreme climates. Experiment 3 examines urban variation within a planned city - the city of Norilsk in the Siberian arctic - through utilising the Soviet Microrayon block; used in cities designed and constructed throughout the 20th century. The formulation of the design problem in experiment 3 is the first that allows for blocks within the superblock to change position and thus break the linearity inherent to the conventional superblock. The population size of experiment 3 further expands on that of experiment 2 by increasing to 26,000 solutions (comprised from 260 generations of 100 solutions each), while the superblock size continues to be comprised from 16 blocks.

Experiment 4 applies all the methods developed in the previous experiments for generating urban variation within an evolved city, utilising a typical urban block located within the city of Fes El Bali in Morocco. Through the experiment conducted, the design problem is reformulated from previous experiments in which the regulation of the phenotype's body parts is focused primarily on the 2dimensional representation of the geometry rather than its 3dimensional representation. In doing so, the computational load is significantly decreased, thus allowing for the size of the superblock to be increased from 16 blocks in previous experiments, to 100 blocks in experiment 4. Additionally, as with experiment 3, the blocks within each superblock are allowed to move, but in this case, they are also allowed to intersect (a process that was too computationally heavy to implement previously). The population size of experiment 4 is similar to that of experiment 3, (25,000 solutions), but the generation size and count drastically differ. Where experiment 3 evolved 260 generations of 100 solutions each, experiment 4 evolves 1000 generations with 25 solutions each.

Finally, the concluding experiments examine the impact of *dynamically* controlling morphological variation ‘live’ within the simulation’s run, in which the data outputted (and their associated analysis) by the solutions evolved in the simulation act as driving mechanisms for directing how much variation is generated by the algorithm. Unlike previous experiments where the analysis conducted on the simulation’s output was performed external to the algorithmic loop, experiment 5 conducts this analysis internal to the algorithmic loop, thus allowing for the reformulation of the design problem at the end of every generation rather than at the end of the simulation. Similar to experiment 1, the analysis conducted is applied within two frameworks, the first being a single objective problem (experiment 5A) and the second a multi-objective problem (experiment 5B).

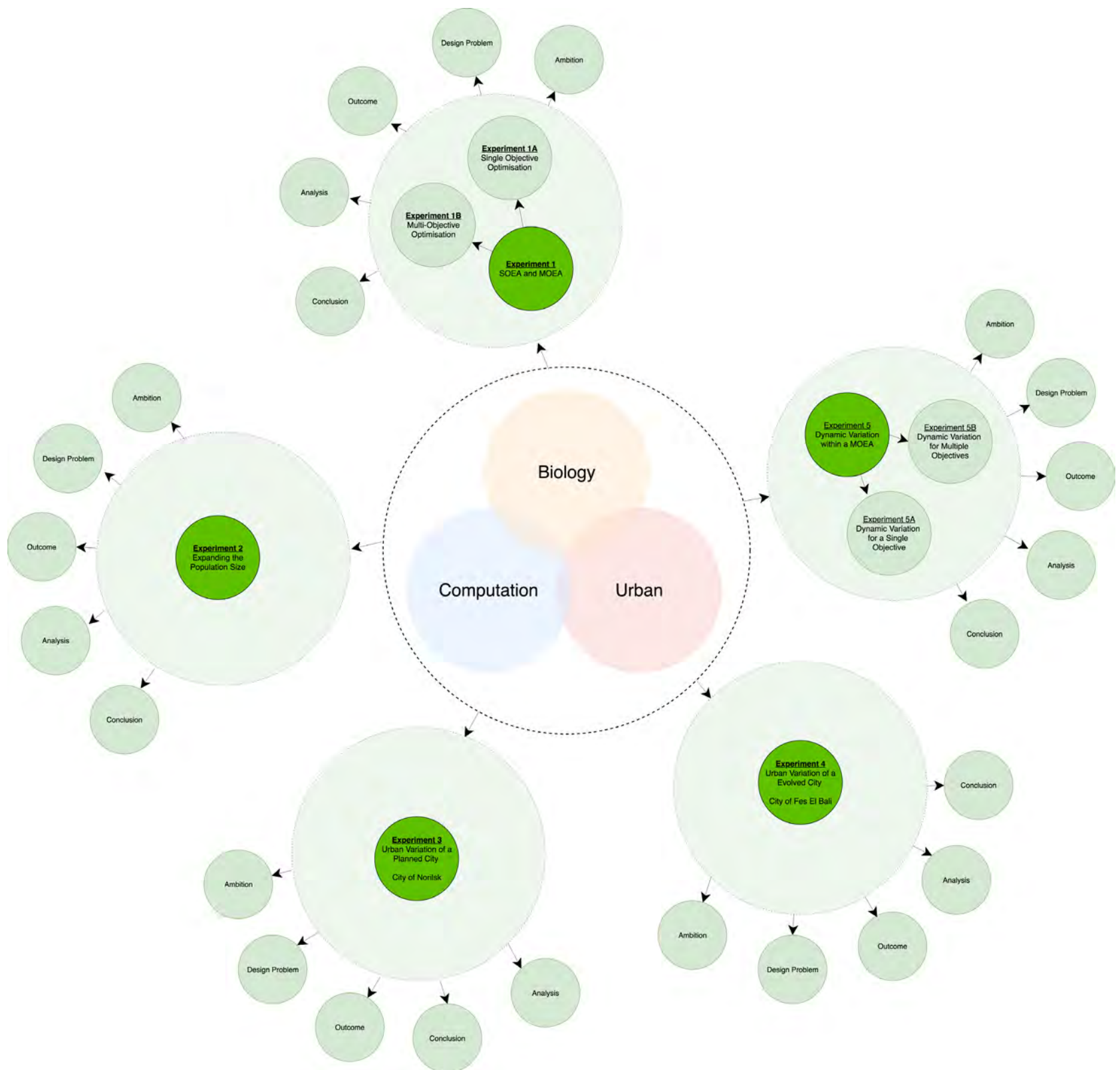


Figure 1.6.
Pseudo Diagram of the Design
Experiments conducted
throughout the research.

Literature Review

2.1. Introduction

The literature review focuses on the intersection between the fields of biology, computation and urban design. However, rather than conducting an extensive and separate analysis of each field, the focus lies primarily in the relationship between the subfields of evolution, evolutionary computation and urban variation and the cross-disciplinarity between these three domains. The objective is to highlight how, and to what extent, the three domains have contributed to one another, and establish new links between the fields that are driven by the independent development within each discipline. A brief summary of the intersection of the fields is outlined below (figure 2.1.).

Evolution and Evolutionary Computation

Biological principles of evolution have played a significant role in developing the field of evolutionary computation. From as early as the mid-20th century, the evolutionary principles of variation and selection have informed computational algorithmic processes towards generating problem solving strategies that have been developed (and continue to develop) to address complex problems within multiple disciplines.

Urban Variation and Evolution

Biology has been used as inspiration countless times within the urban field. Most prominent of which is the association between city and organism. However, where many of these correlations were primarily analogies; in recent times, there has been a link between the phenotypic variation of species driven by environmental adaptation and the morphological variation of blocks and superblocks within the urban fabric that are driven by environmental and climatic stresses.

Evolutionary Computation and Urban Variation

Although evolutionary computation has been applied as a design tool throughout the second half of the 20th century; the relationship between urban variation and evolutionary computation has risen in recent times. This is primarily caused by the recent applications of evolutionary algorithms within generative 3d modelling platforms that allow for the simulation of large data sets (both numerically and geometrically) within a reasonable time frame.

The following sections will examine the three subfields; both independently and in context to one another, to establish the state of the art of each discipline in both their historic and current states. This will serve as the foundation to the development of the research and the experiments conducted throughout.

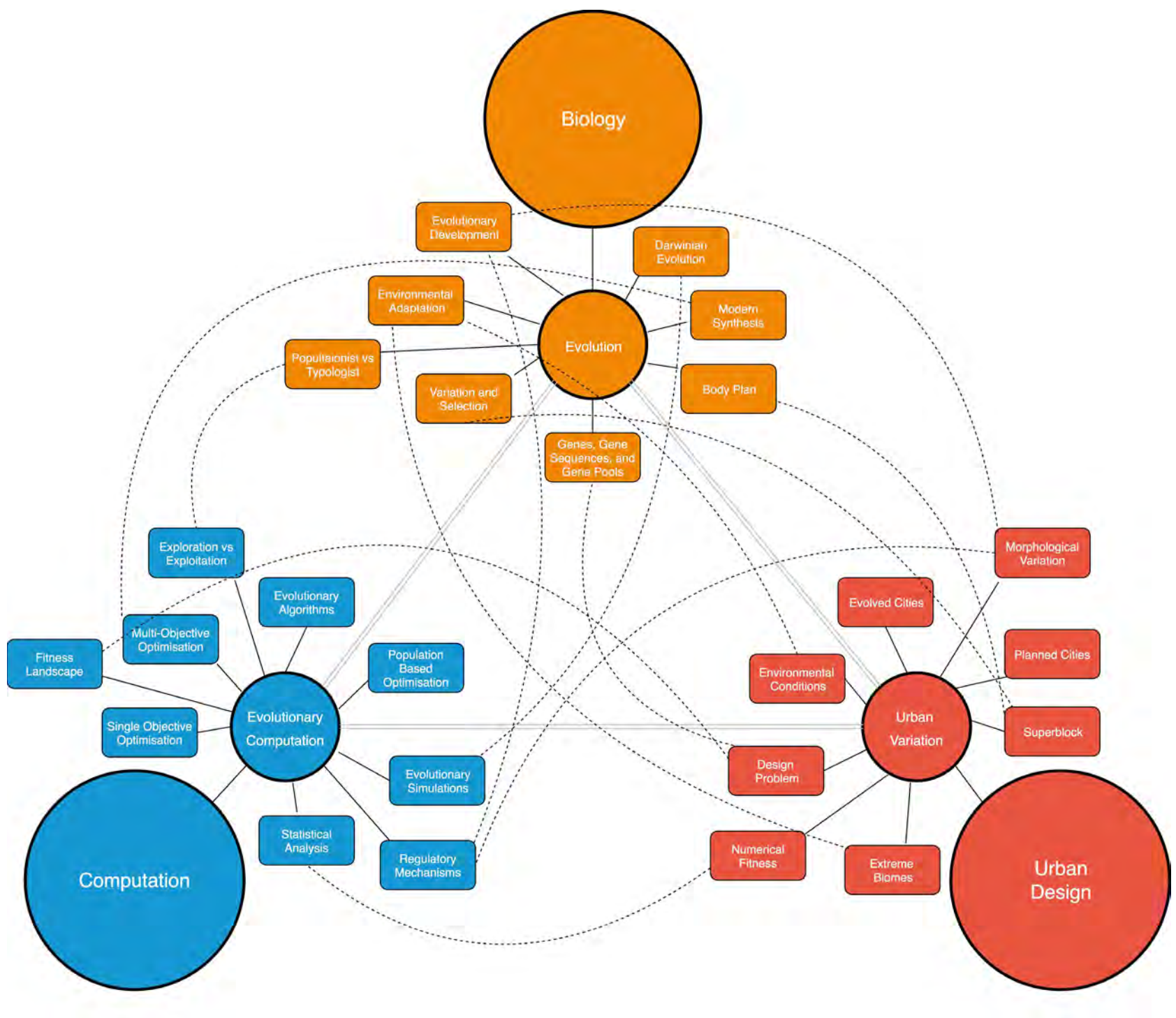


Figure 2.1.
Literature Domain: The intersection between the 3 disciplines of evolution, evolutionary computation and urban variation is the primary focus of the literature review.

2.2. Urban

2.2.1. Urban Growth – An Overview

Prior to the conception of agriculture and food cultivation, settlements have been predominantly mobile, continuously relocating in search for fresh sources of food. Not only did this inhibit these settlements from establishing any kind of permanent residence, but it also had a substantial effect on suppressing population growth. However, with the advent of agriculture and cultivation (a result of favourable environmental conditions caused by the end of the last ice age in 7000 B.C), societies transformed from being geographically mobile, to permanent, as Gordon Childe states that these societies became “...active partners with nature instead of parasites on nature” (Childe, 1946, p. 26) (figure 2.2.). This set in motion the shift from Neolithic societies to the formation of the first cities, a process coined by Childe (1950) as the ‘urban revolution’.

In his book, ‘History of Urban Form’ Morris groups the development of urban settlements from their establishment in the Neolithic age to the industrial revolution of the 19th century into two categories, ‘organic growth developments’ and ‘planned urban developments.’ Morris describes the former as urban settlements that have “evolved without preconceived planned intrusions,” while the latter is described as the “result of predetermined intention” (Morris, 1994, p. 10). Although organic growth was the predominant mode of urban development throughout the urban revolution (approx. 3500 B.C), archaeological discoveries of ‘planned’ cities date as early as 2000 B.C, as evident in the three Harappan cities discovered in the Indian subcontinent (Morris, 1994). However, it was through the Greek Hippodamus and his plan for Miletus in 480 B.C that the process of organisation of new urban entities with a predetermined intention was initiated.



Figure 2.2.
The city of Shibam: The city evolved and survived through changing environmental stresses throughout the past 2 millennia (Maximo, 2018).

Throughout the centuries from the Greek empire to the industrial revolution, there has been a constant dialogue between organic and planned urban development, where one – more frequently than not – was superimposed onto the other. Morris however does not allocate preference of one system or the other; this may be attributed to the fact that prior to the industrial revolution (Morris analyses the history of urban form up to but not including the industrial revolution), both methods of urban development may have been considered to be – to an extent – ‘successful’ in their own way. However, it was the industrial revolution that had the greatest impact on urban development, as it drastically transformed the approach to city planning so as to accommodate the technological advancements of the 19th and 20th centuries.

The industrial revolution has altered city planning into abandoning the traditional urban fabric of the past five millennia towards a modern urban order that accommodated advances in technology, most importantly pertaining to transport (figure 2.3.). This was visualised through Le Corbusier’s ‘urban revolution’, proposing a top-down method of urban planning that was formulated around the automobile, setting in motion the foundations for urban design, a profession established in the 1950s at Harvard university (Farrell, 2013) that became implemented throughout the remainder of the 20th century. However, this movement was met with dissent from as early as the 1960s through Jane Jacobs and Christopher Alexander (separately). Jacobs voiced her criticism of Le Corbusier’s vision by stating that “his (Le Corbusier) city was like a wonderful mechanical toy... but as to how the city works, it tells, like the garden city, nothing but lies” (Jacobs, 1961, p. 23).



Figure 2.3.

City for the car: The effects of the industrial revolution on urban tissues led to the design and construction of cities that were primarily scaled to accommodate transportation (hipwallpaper, 2018).

Although Jacob's criticism of Le Corbusier's modernist planning movement was yet to manifest itself in the 1960s, the present-day environmental impact of the cities planned in the 20th century have provided undeniable evidence that calls for the modernist urban planning methods to be revised. In the opening statement of Stephen Marshall's, 'Cities, Design and Evolution', he states that "Among all species – it is perhaps only humans who create habitats that are not fit to live in" (Marshall, 2008, p. 1). Marshall argues that the 'unplanned' cities of the past have proven to be more habitable, economical and sustainable, creating a correlation between how complex cities function and how functional order is achieved through evolution in nature. Marshall further clarifies that "the 'argument from evolution' suggests that adaptive incremental change can lead to great transformations and a diversity of forms in the long term" (Marshall, 2008, p. 14), further establishing the notion that biological evolution may serve as the most appropriate model for a better understanding of how to plan future cities. In this perspective, the conventional method of urban planning implemented in the 20th century, in which the city was designed not unlike a machine, adhering to an idealistic notion of planning a generic city that is applicable regardless of region, climate or topography, commonly resulted in dire impacts on both global and local scales. In recent years, this has propagated an in-depth analysis of understanding a city within a biological context, an approach introduced as early as the late 19th century by Patrick Geddes (Batty and Marshall, 2009). Thus, developing a city as an organism, through a biological evolutionary model, attempts to establish a substantial and applicable methodology for cities that develop through adaptation rather than optimisation, reflecting traits – already acquired by natural systems – of energy efficiency, environmental response, regeneration and climatic (and cultural) adaptation.

2.2.2. Urban Variation

Variation of blocks and superblocks increases the potential for the urban fabric in which they are embedded to adapt to changes in environmental and climatic conditions and helps to construct patterns of spatial differentiation that are identified with the perception of urban culture and qualities that make a city a good place to live. The Universal city beloved of the early 20th century Modernists has been built everywhere, and all too frequently is simply comprised of a uniform array of a single block type distributed across a grid, with little if any adjustment to specific ecological or environmental contexts. Their attempts to generate substance and quality within the urban landscape through copious amounts of non-contextualised repetition have proven to be unsuccessful. The struggles of the modernist vision for the 'perfect generic city' may be attributed to reasons ranging from climatic conditions to exponential growth in demographics and to cultural pressures; however, the attempt of *predicting* how a city will grow, either morphologically or temporally, may have been the modernists biggest challenge. Although it may be possible to make short term predictions, driven by rules inherent to strategies of urban planning, political influences, economic patterns and social impacts; it is the long-term predictions that are usually impossible to make (Soddu, 2002). Designing an urban tissue that is geared towards permanent configurations defined into everlasting forms, with limited boundaries defined by impenetrable barriers opposes that which is required by a world going through radical changes across multiple frontiers (demographic, climatic, economic, political, etc). The stresses

on future cities demand an approach that enables the urban fabric towards accommodating rapid change, allowing for territories the freedom to communicate and overlap with one another in response to internal and external stimuli within the city's environment (Koolhaas, 1995). Moreover, the successive random and subjective choices made by each inhabitant of the city amplifies the city's unpredictability, imposing a shift in mind-set from understanding a problem to have a single solution, to one that requires multiple solutions, each unique in its own way. In an urban context, this variation is explained as a "formal diversity of solutions responding to the same situations" (Soddu, 2002, p. 112), and although the system cannot be predicted and designed for in advance, it can be addressed through the application of multiple simulations, each generating a *population* of solutions thus bypassing the demand for prediction (which is usually associated with generating a single solution).

This brings forward the need to clearly differentiate between 'the solution' and 'the population'. This is best described within biology, where there is a clear delineation between the 'typologist' and the 'populationist'. Leading evolutionary biologist, Ernst Mayr, highlights their distinction in his essay, *Typological versus Population Thinking*, where he states, "For the typologist, the type (típos) is real and the variation an illusion, while for the populationist the type (average) is an abstraction and only the variation is real" (Mayr, 1997, p. 28). The populationist believes that each solution (or individual) is unique, and by attempting to define a collection of unique solutions through a single representative of the group abstracts the population to a statistical average, one that has lost the individual characteristics that defined each solution within the population. By doing so, an assumption is made that the 'statistical average' solution is the best suited to adapt to the stresses of its environment. The typologist believes that every individual in a population holds the same typical traits, and thus the average individual may be considered as a representative of the entire population. However, a major flaw in the typologists approach is that if all individuals share the same traits, then by consequence, environmental stresses would have the same impact on all individuals alike. However, nature contradicts this, as individuals within a species show significant variation and display unique traits that have evolved differently in response to the same environmental stresses, thus allowing the species to be more robust in the face of changing environmental conditions (it is the variation between individuals of the same population that allow them to adapt differently to their environment). The populationist's approach of signifying importance to variation between solutions rather than an average representative serves as an optimal model for generating variation of design solutions to a design problem that cannot be addressed through a single 'average' design solution, as Mayr states, "An individual that will show in all of its characters the precise mean value for the population as a whole does not exist" (Mayr, 1997, p. 29) (figure 2.4.).

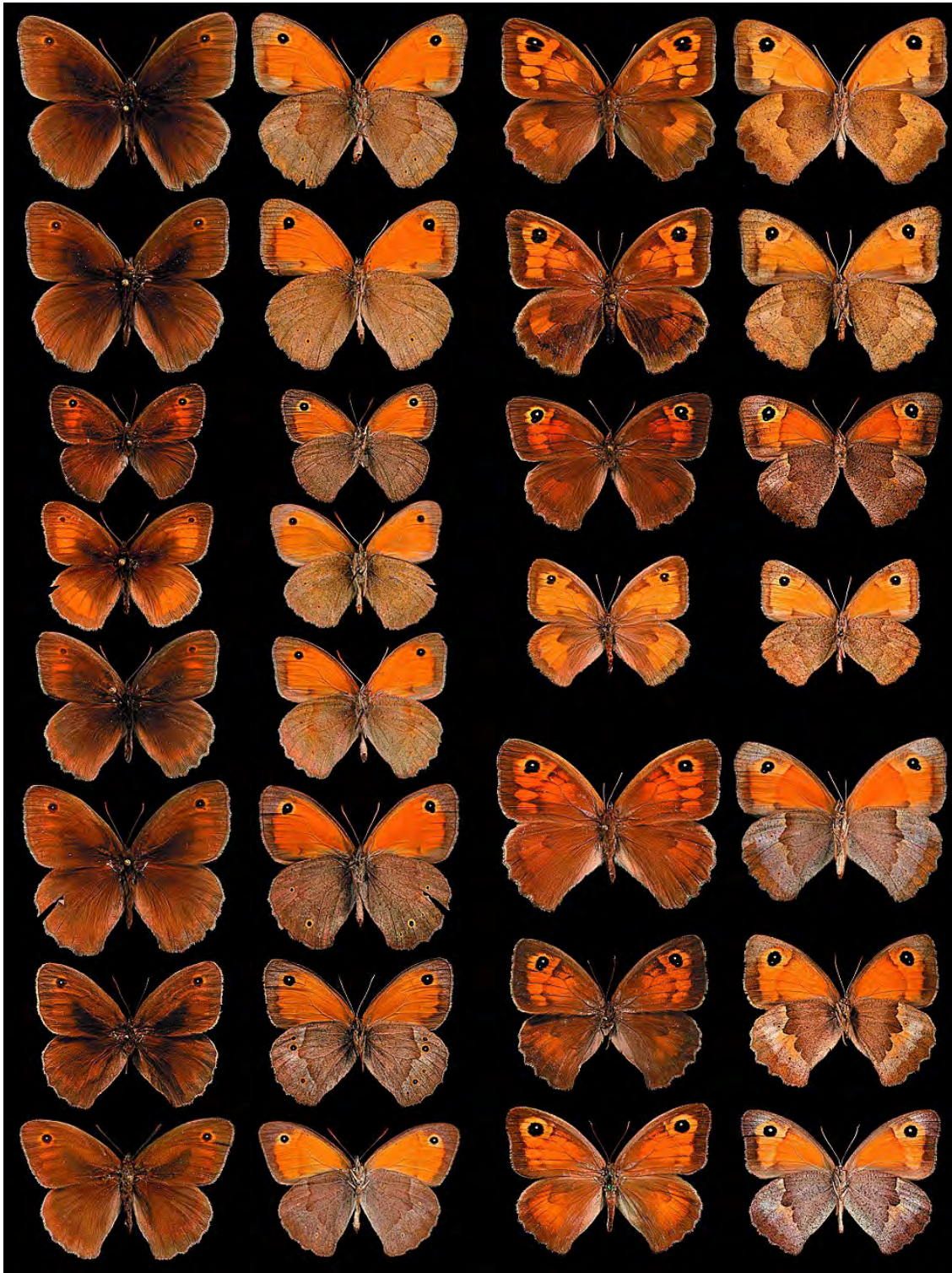


Figure 2.4.
Variation in Nature: Within the same species, there exists morphological variation between phenotypes that is attributed to genotypic variation between individuals of the same population. Each individual is unique, an 'average' individual cannot be selected to represent and carry forward the genome of the entire population (Grill and Vos, 2004).

Today rapidly changing climatic conditions and the exponential growth and mobility of populations, are accelerating changes to the environmental context of many cities across the world. There are some cities that evolved over many centuries that have adapted over the course of their history to changes in their environment and climate; surviving and continuing to grow over several centuries within their environment. However, changing the built forms and spatial patterns of a city is a slow process. Although in the past there have been some cities that have been able to adapt to different climatic conditions at a rate relative to the rate of change in their context; the rate at which the climate is predicted to change over the next 50 years is accelerating (Dusik, 2018); and so it is widely thought that there is insufficient time available for mature cities to adapt (figure 2.5.).

The challenge lies in developing a computational process that is capable of generating adequate variation of urban morphology that is optimal for multiple conflicting objectives. One widely used approach to multi-objective computation is for the designer to give greater weighting to one objective over the others, or to vary the reactive importance of the objectives in a cascading rank. This makes the process deterministic on the initial conditions and decisions of ranking. What if the initial conditions were to change during the computation?

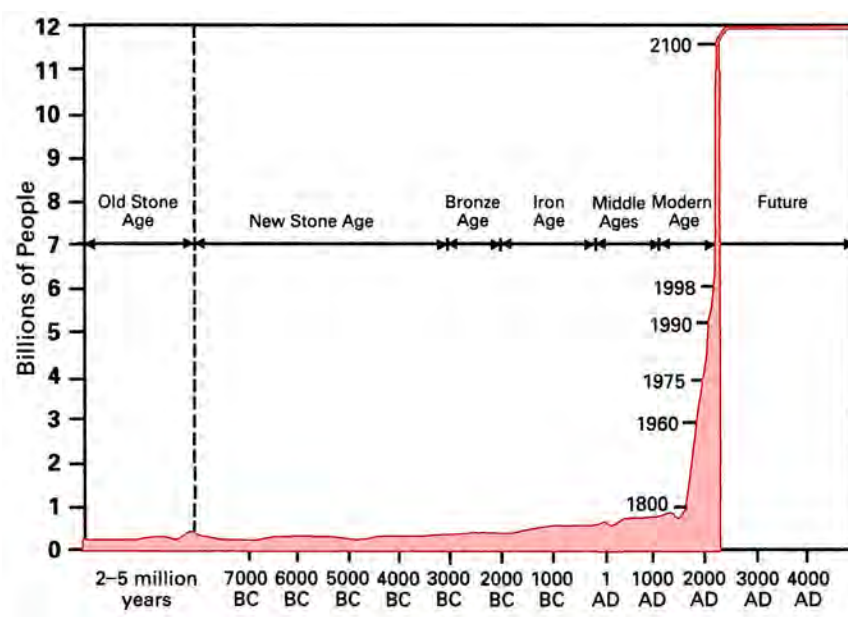
It is possible to incorporate a feedback control operation that modifies itself through time as it converses with a continuously shifting landscape, thus maintaining an equilibrium state when met with continuous change (De Jong, 2016). Natural biological evolution offers a model of a system in which populations have adapted to changing environmental and climatic conditions without direction or designer bias. Precedence for the application of an evolutionary model as a problem-solving strategy dates back to the early 20th century. It has since developed into a model that has been applied in a multitude of different fields to provide solutions to problems that required objectivity, optimality and efficiency.



Figure 2.5.
Morphological Variation plays a significant role in increasing the robustness of Urban Form against climatic and environmental stresses (image from the Fes El Bali Urban Tissue, evolved in experiment 5 of this thesis)

2.2.3. Climatic Impact on Urban Development

Rapidly changing environmental and climatic conditions, coupled with the growing numbers in urbanised populations, has stressed the ability of existing cities to cope with these sudden and highly impactful changes. The critical threshold of stability (Weinstock, 2010) in which a city's population grows beyond its maximum capacity, thus straining its resources and ecological demand, transforms the city to one that is highly sensitive to changes in its environment (figure 2.6.). Although this is a scenario that has repeated itself multiple times across different geographic locations and time periods, its occurrence in modern day carries with it dire impacts as the rate of change to climatic and environmental conditions is one that is unprecedented. The adaptation of cities that have approached their critical threshold is highly contingent on the rate of change in the environment; historically, the rate of environmental and climatic changes allowed for cities to evolve in response to these changes. However, the rate of environmental and climatic changes observed in the 20th century, and predicted throughout the 21st century, coupled with the exponential rate of population growth (including the migration of people from rural settlements to urbanised ones) highlights the necessity to re-evaluate the city's ability to maintain a balanced relationship between the internal processes that govern the city's growth and development and its environment.

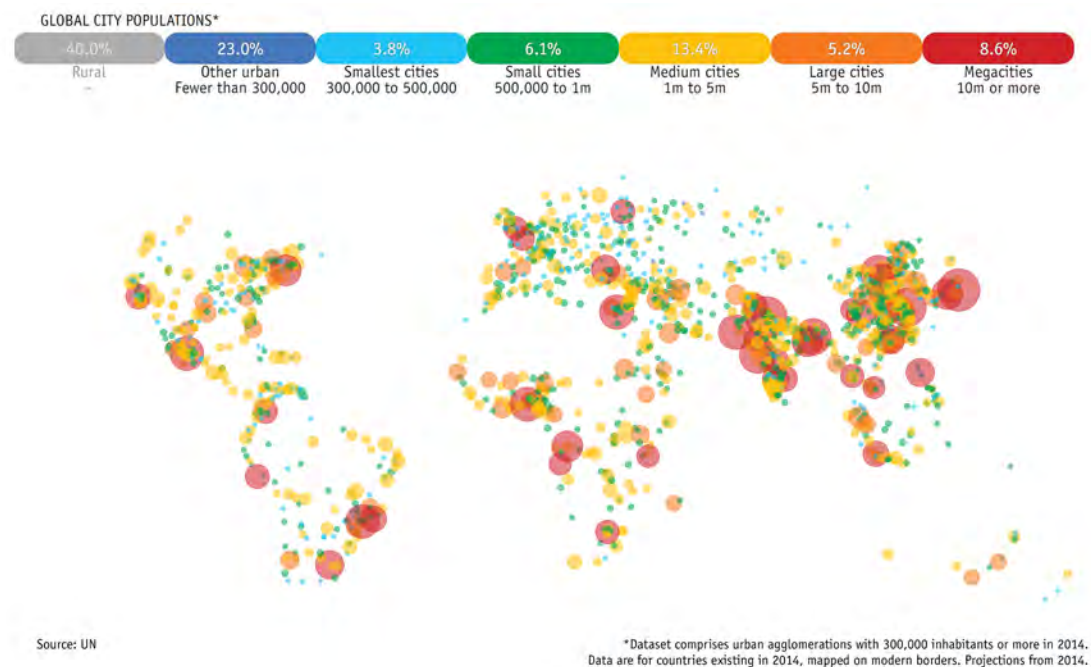


The IPCC's report on the unprecedented impact of the changing climate on global warming, rises in sea levels, desertification and the frequency and intensity of short lived yet highly impactful extreme events (such as hurricanes, monsoons and floods) is predicted to continue to increase throughout the 21st Century, and is projected to have dire impacts on human and natural systems worldwide (IPCC, 2014a). Greenhouse gas emissions (the leading cause of

Figure 2.6.
Population growth through history: All natural systems experience a 'surge' in growth that leads to the system exceeding its carrying capacity, what follows is either a sudden drop in population numbers, or constant fluctuation around the populations carrying capacity (McFalls Jr, 1991).

global warming observed in the 20th and 21st centuries) resulting from growing economies and populations are the highest on record, and are expected to continue to grow in line with the growing world population (IPCC, 2014a). Future pathways towards adaptation and mitigation will cause significant reductions in emissions, leading to reduced climatic risks projected throughout the 21st century (Masson et al., 2014). However, mitigation takes precedent over adaptation; where the latter may reduce risks associated with climate change, it is less effective in cases accompanied with larger rates and degrees of a changing climate. In contrast, without effective mitigation, “warming by the end of the 21st century will lead to high to very high risk of severe, widespread and irreversible impacts globally” (IPCC, 2014a, p. 17).

Although urban areas cover a significantly small portion of the earth’s surface, only 2% (UN Habitat, 2018), they are the leading cause of climatic warming, where they “account for between 71% and 76%” (IPCC, 2014b, p. 927) of CO₂ emissions worldwide. By 2030, the number of cities that hold 1,000,000 inhabitants are projected to increase by 30% (from 512 to 662), and the number of megacities (cities with populations of 10,000,000 or more) are expected to increase from 31 to 41 within the same time-period (Tollin et al., 2017) (figure 2.7.). Without the implementation of any adaptive or mitigative efforts, the percentage of CO₂ emissions from urban areas is expected to rise dramatically throughout the 21st century. The Worldwatch institute attributes one of the primary causes of urban CO₂ emissions to urban sprawl, in which a city’s footprint expands as a result from its overdependence on vehicular transportation. More importantly, there is a non-linear comparison between the rate of urban sprawl to population growth; where in some instances a city’s land area tripled in response to a 30% increase in population (Worldwatch Institue, 2001). In an attempt to curb the impact of urban landscapes on climate change, the modernists city that was designed to accommodate the vehicle through repetitive grid-like blocks and superblocks must be abandoned, and instead, an alternative that employs walking distances and integrative public transport as design drivers for the city’s growth and development (Sheehan, 2001). More importantly, the infrastructure required to accommodate the rising population numbers will have an exponential impact on climate change; as in doing so, the expansion would result in the release of 4 times the amount of CO₂ emissions into the atmosphere when compared to the amount that has already been released when the existing infrastructure was being built (Bai et al., 2018). As such, the science of cities has evolved towards understanding cities as complex systems, comprised from complex local interactions between the individual elements that comprise the city (Marshall, 2008), thus allowing for an alternative strategy for managing risks associated with climatic adaptation and mitigation.



2.2.4. Evolving Cities Versus Planned Cities

The argument against modernist planning emerged within a relatively short period of its inception, with Jane Jacobs (1961) in her book *The Death and Life of Great American Cities* and Christopher Alexander (1965) in his PhD thesis *Notes on the Synthesis of Form* being one of the first to voice their dissent against the movement (Batty and Marshall, 2009; Marshall, 2008). There was a clear distinction between cities that have developed through theories of self-organisation and emergence, leading to complex systems that could not have emerged otherwise, and cities that have been planned through a top-down approach, with the aim of developing a finite and 'perfect' urban form. One of the clearest arguments put forward to differentiate between the two approaches was by Christopher Alexander (1964) in his paper *A City is not a Tree*, in which he attributes "artificial cities" to a tree, and "natural cities" to a semi-lattice, where both models are examples of how a large, complex system is comprised from many smaller systems working together. Although Alexander's conclusions were clear about which system he believed to be more robust, he nonetheless compares them in terms of their complexity, and how it is achieved through the sum of its parts.

There has been a favourable shift towards understanding urban change and development through complexity science; the predictability inherent to the classical science's approach to urban change has been incapable of developing a system that is intrinsically emergent, adaptive, and unstable, one that is in a continuous state of change and imbalance (Batty, 2008). Designing a city by means of a top down approach that attempts to create a single, optimal solution omits

Figure 2.7.
Urbanised Populations:
The number of the world's megacities that will house populations of over 1,000,000 or more will dramatically increase due to both population growth and the shift from rural populations to urbanised populations (The Economist, 2015).

the complex variance and dynamism that is essential for a city's growth and adaptive change. Ferrell (2013) argues that a city cannot be designed by a single or group of planners, as in the past, this has led designers "to treat the city as a simple mechanistic tameable object - invariably with disastrous consequences" (Farrell, 2013, p. 33), replacing spontaneous urban growth with a top down method of design, inevitably leading to the detachment of the inhabitants from their environment (figure 2.8.). In contrast, when approached through a Darwinian evolutionary model, the characteristics associated with the growth, development and adaptation of natural systems and their application in design becomes more tangible (Steadman, 1979, 2008).

Although correlations between biology and the city have been made throughout history, it is only recently that these correlations have shifted from simple analogies to analytical and generative applications. This has been a result of understanding that repetitive localised decisions that mutate and adapt with every iteration in response to external interactions are what form the collective whole, and so instigating small changes at this 'sub-system' level allows the collective to evolve in response to the sub-system's *reaction* to their external pressures (Hamdi, 2004). From an evolutionary perspective, the city is not designed as a single complete and finite entity, rather it is approached as an assembly of reciprocal, dependent and interactive co-evolving parts. Therefore, rather than inhibiting city growth, and so by consequence its adaptation to external stresses from its environment, a bottom up emergent approach enables the city to develop diversity and variation in its urban form which in turn equips it with developing a stronger adaptive dialogue to its environment (Batty and Marshall, 2009).



Figure 2.8.
Abandoned cities as a template for growth: Planned cities constructed to house rising population numbers utilise the generic block that is repeated across the landscape. These cities remain uninhabited even though they are complete (right: Ordos city in China). Regardless of their failure, they are repeated in cities worldwide (left: Kilamba city in Angola) (Miklós, 2013; CITIC Construction, 2012).



2.2.5. The Superblock and Its Significance

The block has been utilised as a spatial tool considered to be the most basic element of a city's development. Its evolution is traced back to early migratory groups that occupied pit houses (or in some cases courtyard houses) that were well adapted to both the environmental and climatic conditions and the population's cultural values. Their distribution (and relationship thereof) developed into becoming the dominant organisational urban element that formed urban settlements. However, as urban tissues continue to grow, the basic element of the block has become nested into forming what is referred to as a superblock; a collection of blocks that are related to one another through their formal distribution and morphological properties. As the scale and the capacity of the urban tissue continues to expand, these superblocks become interrelated at a regional level evolving into urban patches of varying sizes.

There are countless examples of nested blocks that vary in size, morphology and occupancy; in the case of the ancient Greek city of Miletus, blocks – primarily in the form of courtyard houses – were approximately 30m x 30m in footprint. While in 15th century Beijing, courtyard blocks were nested in a 150m grid throughout. In modern day Barcelona, the block with inner courtyard has increased in size to occupy a footprint of 100m x 100m, distributed throughout the city in the form of superblocks that have become core to Barcelona's urban landscape (figure 2.9.).

In contrast to historical precedents, modern day examples of superblocks are predominantly uniform in size, distributed in equal uniformity across the urban landscape. However, many evolving cities exhibit blocks and superblocks that vary substantially in both their morphology and distribution. Through sampling different urban patches (both evolving and planned), one can extract a block's (or superblock's) specific formal features and traits. Case in point, the city of Fes in Morocco, a city evolved through its blocks' strong adaptability to its environmental, climatic and geographic context, while encoding within the formal distribution of the city's block's a spatial representation and value of its people's culture.

David Grahame Shane (2011) describes the superblock as an enclave that is bounded by space and defined by a perimeter with clear access points and distinct centre. As an urban organisational tool, it carries with it several urban functions and processes that serve as the basis for adaptability to environmental and climatic change. Thus, its functionality, morphology and infrastructural qualities are crucial to its impact on its surrounding ecology.



Figure 2.9.
The Urban Superblock: The Eixample superblock (top image) and the Hutong superblock (bottom image). Using the superblock allows for an urban unit that is large enough to incorporate relationships between blocks, yet small enough to ensure that sufficient variation is maintained between each block in the superblock.

2.3. Evolution

2.3.1. Evolutionary Thought

Charles Darwin's theory of biological evolution is considered as one of the most prominent and influential findings of modern science (van Wyhe, 2016; Arthur, 2011; Shane, 2011; Futuyma, 2009; Marshall and Batty, 2009; Carroll, 2005; Carroll et al., 2005; Ridley, 2003; Mayr, 2002), holding a profound impact across multiple disciplines and giving rise to the development of new disciplines, ranging from ecology to alternative approaches to psychology (Marshall and Batty, 2009). However, the roots of evolutionary thought have a greater historic foundation, one that predates Darwin by many millennia through the work of Heraclitus (480 B.C.E) and Empedocles (430 B.C.E) in which they believed that organic change is the root of all life (Smocovitis, 2016). Scientists as early as the 13th century theorised that species with beneficial characteristics or physical traits are more advantageous in surviving than species without these traits (Nasir Al Din Al Tusi, in his book *The Nasirean Ethics*) (EES, 2018), and then later in the 14th Century in which the Arab historian Ibn Khaldun suggests that all natural systems and species descended from one another, where each species or natural system precedes the next, whereby they are all "connected"; clarifying that "the word 'connection' with regard to these created things means that the last stage of each group (*each species*) is fully prepared to become the first stage of the next group" (Khaldūn Ibn, 1958). The rich history associated with evolutionary thought sought to explain how and why so much morphological variation, across and within, different species existed, and what role, if any, the environment played in developing and differentiating these morphological traits.

Although the debate continues, there has been a consensus within the scientific community that Darwin's theory of evolution of 'descent with modification by means of natural selection' lay the foundations to evolutionary thought. This is exemplified through their presence as a corner stone in the modern synthesis. It is these two theories that have eluded many researchers prior to Darwin. Understanding the primary mechanism behind evolutionary change through the process of the adaptations of individuals within populations, over the course of multiple generations, in response to environmental pressures through the selection of beneficial traits and the 'discarding' of harmful traits, is essential for the analysis and application of evolutionary thought as a developmental and/or generative model.

Differentiating between the *Genotype* and *Phenotype* is fundamental to gain a clear understanding of how natural selection works (this is crucial as it will formulate the processes by which the experiments conducted within this thesis are conducted). Within an organism, the genotype (or genome) is its genetic code; it is the 'blueprint' that is used to develop and construct the phenotype (or phenome), which is the composition of the organism's physical characteristics. The primary distinction between the genotype and phenotype is that of variation and selection. The former applies on the genotype, through the transfer of genetic information from parent to child, or through mutations that happen to the genetic information during the genetic transfer. The latter applies on the phenotype, where the formal and physical manifestation of the genetic

changes interact with the environment, thus determining whether these changes were either beneficial, neutral or harmful for its survival. Therefore, within an evolutionary process, selection is determined by changes (or genetic variants) that occur in the genotype, and the impact of these changes on the phenotype (Proulx and Østman, 2016).

The genetic variants that take place in an organism's genotype are key in determining the phenotype's *fitness* in the population. The fitness of an individual is a measure of its success in surviving and reproducing, which in turn allows it to transfer its genetic makeup (or parts thereof) to the next generation. *Positive selection* is when the genetic variant is beneficial, causing a morphological trait to emerge in the phenotype that contributes to increasing its fitness within the population, thus increasing its chances for selection and by consequence the selection of the beneficial genetic variant. In contrast, *negative selection* is when a genetic variant is harmful (or deleterious) and causes a phenotypic change that decreases its fitness within the population; in this case, selection acts to remove the deleterious variant from the population by inhibiting the organism's chances of survival and reproduction. A third variant, *neutral*, is when the genetic change is neither beneficial nor harmful, thus not affecting the individual's fitness nor its chances of survival (Racimo et al., 2016). Neutral genetic variants may spread and become *fixated* in the population due to random chance. An analysis of the distribution of genetic variants distributed throughout the population are key in understanding how organisms have adapted to changes in their environmental conditions (figure 2.11).

The measure of an individual's fitness is dependent on the population the individual belongs to. In an unlikely case that all individuals in a population share the same fitness (if we were to presume that a single individual is a representative of the entire population), selection will not be able to differentiate between the individuals, in turn having no impact on the evolutionary process. As such, a statistical analysis of the population's fitness determines the mode of selection being employed (figure 2.10.). *Directional selection* is when a population's mean fitness either increases or decreases as a result of many individuals with a higher relative fitness to the mean, this causes the population's overall fitness to change in the direction of the 'majority'. *Stabilising fitness* is when the phenotypes converge towards a group of fit individuals, thus decreasing the phenotypic variation throughout the population. In contrast, *Disruptive selection* is the direct opposite, where phenotypes equally diverge from the population's mean fitness, thus increasing variation. In both stabilising and disruptive selection, the mean remains more or less unchanged, with the variation of individuals (and by consequence, the fitness distribution) within the population that is mostly affected (Wood and Brodie, 2016).

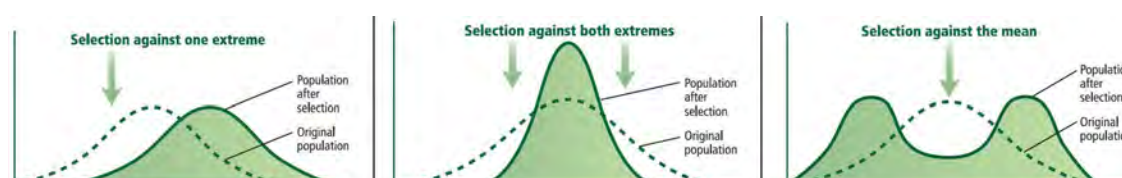


Figure 2.10.
Direction, Stabilising and Disruptive Selection: The analysis of variance and the standard deviation within the population represents the type of selection being imposed on the population (Kubuske, 2014).



Figure 2.11. Phenotypic Selection and Variation: Species react to stresses from the environment, changes in these environmental conditions have an impact on the morphological characteristics of a species that are deemed beneficial and thus selected for; therefore, the fitness of the species is dependent on having within the population diversity between its individuals, in doing so, the species is more robust and has a higher chance of survival against a changing environment (Pham, 2018; Debivort, 2006).



2.3.2. The Modern Synthesis

Charles Darwin's 'The Origin of Species' was published in 1859, proposing an explanation for the plethora of variation in nature. Darwin noted several characteristics for the process of evolution, most prominent of which were the following (Mayr, 2002):

- The non-constancy of species (the basic theory of evolution).
- The descent of all organisms from common ancestors (branching evolution).
- The gradualness of evolution (no saltations, no discontinuities).
- The multiplication of species (the origin of diversity).
- Natural Selection.

Sean Carroll (2005) argues that it was two of these 5 theories that comprise the essence of Darwinian evolution, 'descent with modification' and 'natural selection'. Carroll States that "Natural selection for incremental variation forged the great diversity of life from its beginning as a simple ancestor" (Carroll, 2005, p. 31). Carroll further simplifies Darwinian evolution down to three main components "Variation, selection and time" (Carroll, 2005, p. 33). Carroll clarifies these three components in context, by which a small difference (variation) amongst individuals, compounded by natural selection (selection) over a period of time (time) adds up to the large differences we observe between species today.

On the other hand, Mayr categorizes Darwin's 5 major theories of evolution in terms of their acceptance amongst scientists. Mayr (2002) states that the first 'Darwinian revolution' was the acceptance of the theory of evolution and the theory of common descent, both of which were accepted with little defiance by scientists. However, there was greater resistance in accepting the theories of gradualism, speciation and natural selection, which, once accepted, established the second 'Darwinian revolution'. The acceptance of these 5 Darwinian principles culminated in establishing of the 'Modern Synthesis' (also known as the evolutionary synthesis or synthetic theory) by key evolutionists in the 1940s. The modern synthesis was the union of theories, as well as the discrediting of other theories, that provided a unified and accepted account of evolution amongst scientists, reaching a state of a unifying discipline that demonstrated meticulous and exhaustive experimentation and quantification (Smocovitis, 2016). Mayr (2002) highlights three main accomplishments of the modern synthesis:

- "The rejection of the three evolutionary theories competing with Darwinism:
 - Orthogenesis (finalism).
 - Transmutationism (based on saltations).
 - Inheritance of acquired characteristics.
- Integrated adaptation (anagenesis) and organic diversity (cladogenesis).
- Confirmed Darwinian variation and selection while invalidating any criticism of it."

2.3.3. Novelty and Variation Through Genetic Regulation

Genetic variation is one of the most important factors driving evolutionary change; it is the genetic makeup of an organism (its genotype) that determines the phenotype's characteristics, and so without genetic variation within the genotype, and more importantly, between the genotypes of different individuals within the population, the differentiation and selection of individuals, which is central for an evolutionary process to take place, becomes non-existent (Hollocher, 2016). Therefore, it is unsurprising that genetic variation is significantly present in the genetic makeup of all diploid (and some haploid) species (Spencer, 2016). The *selectionist paradigm* argues that the reason for copious amounts of genetic variation within species is due to the beneficial impact of variation on the individual's selection for survival and reproduction, as it equips the individual with a larger 'toolset' in the face environmental change, therefore providing it with a *selective advantage* over other individuals within the population that have lesser amounts of genetic variation (Lacy, 1997).

The significance of genetic diversity within a population has been documented to contribute to increased adaptability to changing environmental and climatic conditions in addition to heightened fitness levels across generations. A population that has evolved within any particular environment will have the majority of its individuals close to optimal fitness but will also have a significant fraction that are genetically and morphologically different, or varied, from the norm, and so are less 'fit'. When environmental and climatic conditions change, those formally optimal or 'fittest' individuals will now be less fit for the new conditions, but amongst the formerly 'less fit' individuals there will be some that are better matched to the new conditions, and so they become the new 'fittest'. They will prosper and over time their genes will propagate through the population until they become the dominant gene set. It has been argued genetic diversity in a population is significant in three ways, "The importance of species diversity for ecosystem functioning; the importance of genetic diversity to predict the vulnerability of a species to extinction; and the importance of genetic diversity for survival of populations within a species" (Booy et al., 2000). Each of the three is interdependent on the level of fitness – both individual fitness and fitness of the population as a whole.

However, some authors (Schemske et al., 1994; Lande, 1988) argue that the contribution of genetic variation to a population's adaptability is more evident over a long period of time and less so in the short run; thus putting forward the notion that the effects of higher rates of genetic variation across multiple generations contribute to the robustness of a species survival in the face of environmental stress factors.

There is a central difference between genetic variation within an individual's genome to the genetic variation between the genomes of the individuals across the population; this difference is assessed with regards to the rate of adaptation of these species to changes in environmental and climatic conditions. As the amount of genetic variation within an individual's genome is limited (mainly to the genome's length and inherited traits), the genetic variation between

individuals of the same species occurs at higher frequencies relative to the single individual; Den Boer et. al., (1992) argues that “this means that a population can only achieve its adaptability by distribution of the variation across individuals.”

In addition to contribution of genetic variation to environmental adaptability, there is also an impact of environment on gene expression of the phenotype. This can enable some species to react to environmental and climatic changes without the necessity of genetic changes (Booy et al., 2000), This is a widespread phenomenon in plant species known as ‘phenotypic plasticity’ (Gause, 1947), and is an additional contributing factor to a population’s ability to adapt to its environment (figures 2.12 and figure 2.13).

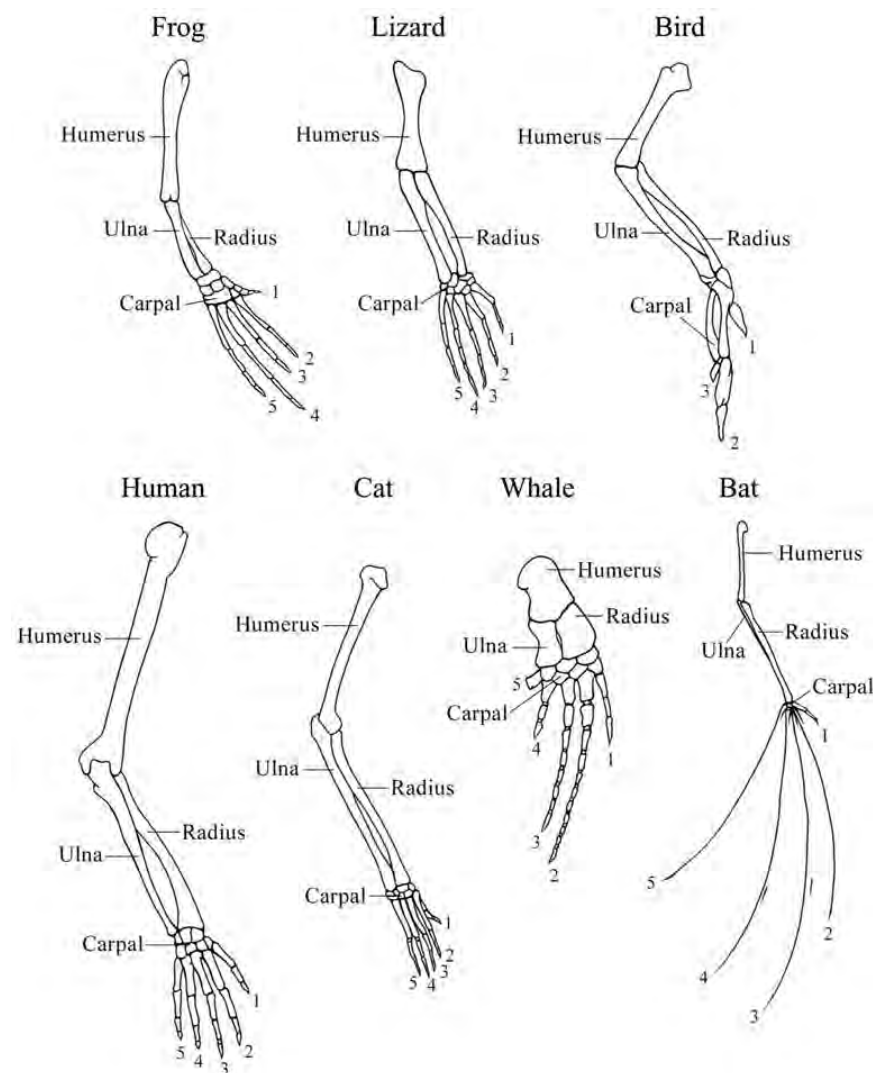


Figure 2.12.

Diversity of Homologous Parts: Species that exhibit traits of modularity are the most diverse groups, highlighting the ability of instigating morphological change in some parts of the phenotype without affecting other parts of the body (Carroll et al., 2005).

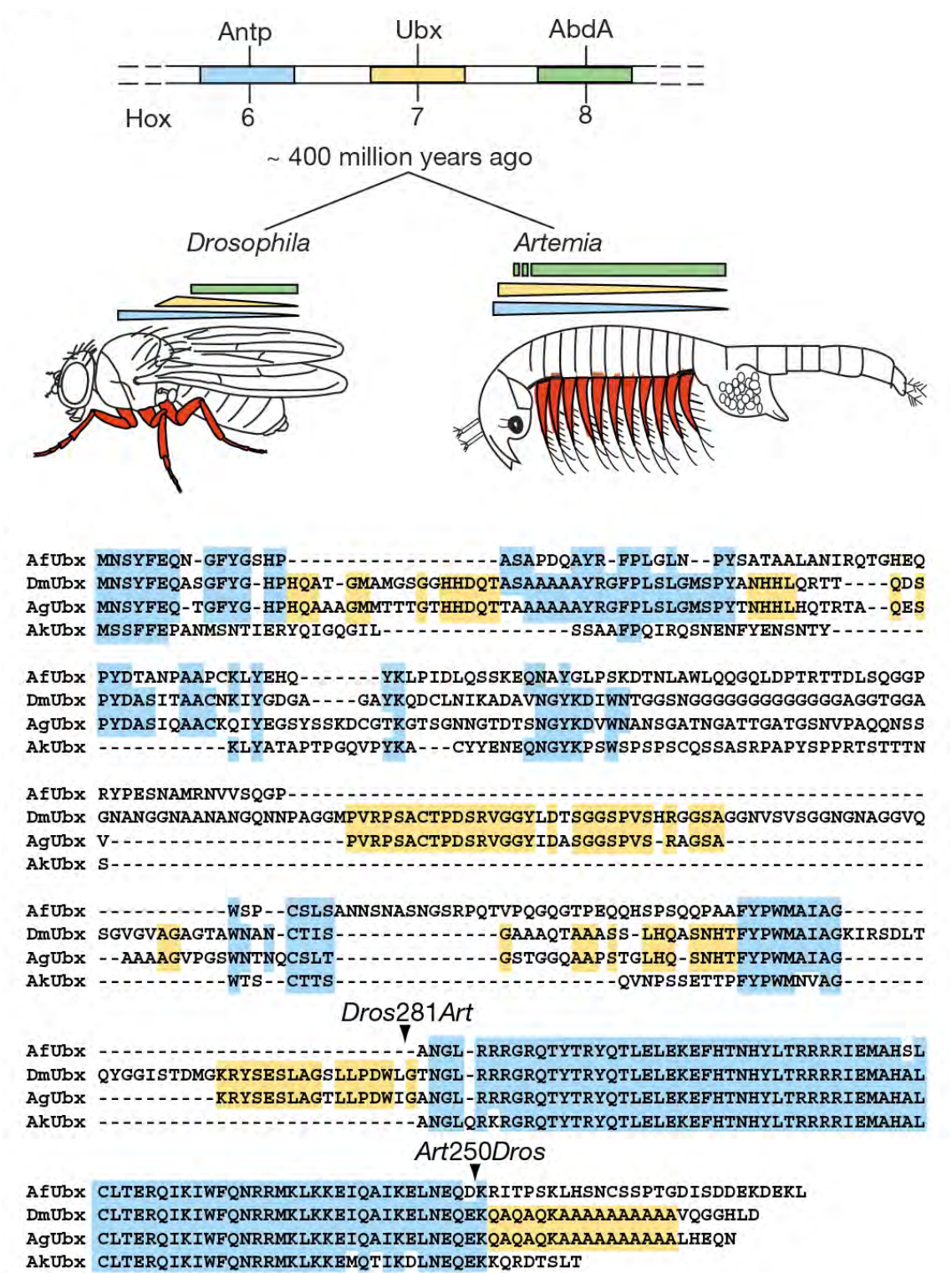


Figure 2.13. Regulation and novelty: The body plan and the regulation between genes and body parts are believed to be the cause of major changes in the evolutionary lineage between species. Through suppressing some genes, a cascading affect on related genes drastically transforms the phenotype morphology. The study in the figure demonstrates how six legged insects diverged from crustacean arthropods 400 million years ago due to the expression of existing genes (as opposed to their duplication or deletion) (Ronshaugen et al., 2002).

2.3.4. Evolutionary Developmental Biology (Evo-Devo)

In formulating the modern synthesis, and in the several decades that followed, it was generally agreed that the main cause of morphological evolutionary variation was changes and variants to protein coding genes, in which a mutation (its duplication, deletion, translocation, etc..) would cause the gene to generate a varied morphological trait when compared to the original phenotype (Wittkopp and Kalay, 2012). One explanation for this is the knowledge and tool set at the time made this research direction easier to study (Sadier, 2016). The claims made through this research were challenged through the discovery of regions in the DNA that played a regulatory role, in which they controlled how much a gene was expressed during the developmental stages of an organism. The discovery of these regions, called cis-regulatory regions, put forward a stronger argument that better explained phenotypic diversity and novelty amongst species (Carroll, 1995). The role of cis-regulatory regions on morphological variation was strengthened in the 1980s through the discovery of the hox genes, the genetic toolkit that controlled the development and formation of the body plan, which regulated which genes were expressed at different parts of the body and at which stages of the developmental process (expressing a gene early on in the developmental process would have a greater effect than if it was expressed at later stages of development). More importantly however, it was discovered that this genetic toolkit is preserved across different species, in which it defined the body plans through the exact same process, regardless of phyla. Further research elaborated on the role of the genetic toolkit beyond the confines of differentiating body parts and establishing a clear body plan, the toolkit was also responsible for developing morphological traits as modules, where each module held its own toolkit (Schneider and Amemiya, 2016) (figure 2.14.).

Although it was hypothesised that changes in developmental mechanisms were primary for morphological evolution (Raff and Kaufman, 1983; Gould, 1977), the discoveries of regulatory regions, and the research conducted on the significance of variants (mutations) on gene regulatory networks for morphological novelty, were central to establishing a strong foundation for the influence of biological development in the evolutionary process. Where the original attempts to explain morphological variation depended on many mutations occurring on a gene until a novel trait evolves (or disappears), evo-devo was able to explain this novelty through a more efficient process; mutations occurring in gene regulatory networks allowed genes to be expressed or repressed (or switched on and off) thus instigating a cascading effect on all genes that were controlled by that regulatory mechanism. An example of this is in the research by (Ronshaugen et al., 2002), where they were able to explain the divergence of six legged insects from their crustacean arthropod ancestors through the mutation of regulatory mechanism which in turn expressed and suppressed the genes involved in the development of their respective abdominal segments. Whereas another research conducted by (Shigetani et al., 2005) explained the emergence of the vertebrate jaw in the evolutionary timeline was a result of a mutation that shifted the location of an expressive regulatory gene (further examples on the evolution of novel phenotypic traits resulting from regulatory changes within the genome can be found in (Love and Urban, 2016) and (Sadier, 2016)).

The research conducted through the field of evolutionary development was successful in investigating and explaining the construction of novel structures, and the development of morphological variation through the study of the gene regulatory networks *in addition* to the genes themselves (Love and Urban, 2016). This has led to alternative definitions of *novelty*; novelty can be viewed as the potential for phenotypic variation through variants in developmental mechanisms, thus emphasising the role that development, and the consequent regulation of different genes to different body parts, has on the phenotype (Wagner and Zhang, 2011). While another definition explains that by having a robust developmental tool-kit, it increases the eco-system’s carrying capacity to be better equipped for adapting to changing environmental conditions (Erwin, 2012). Both definitions highlight the significance and profound impact that evolutionary developmental processes have on the ability to evolve novel and varied morphological traits within the population.

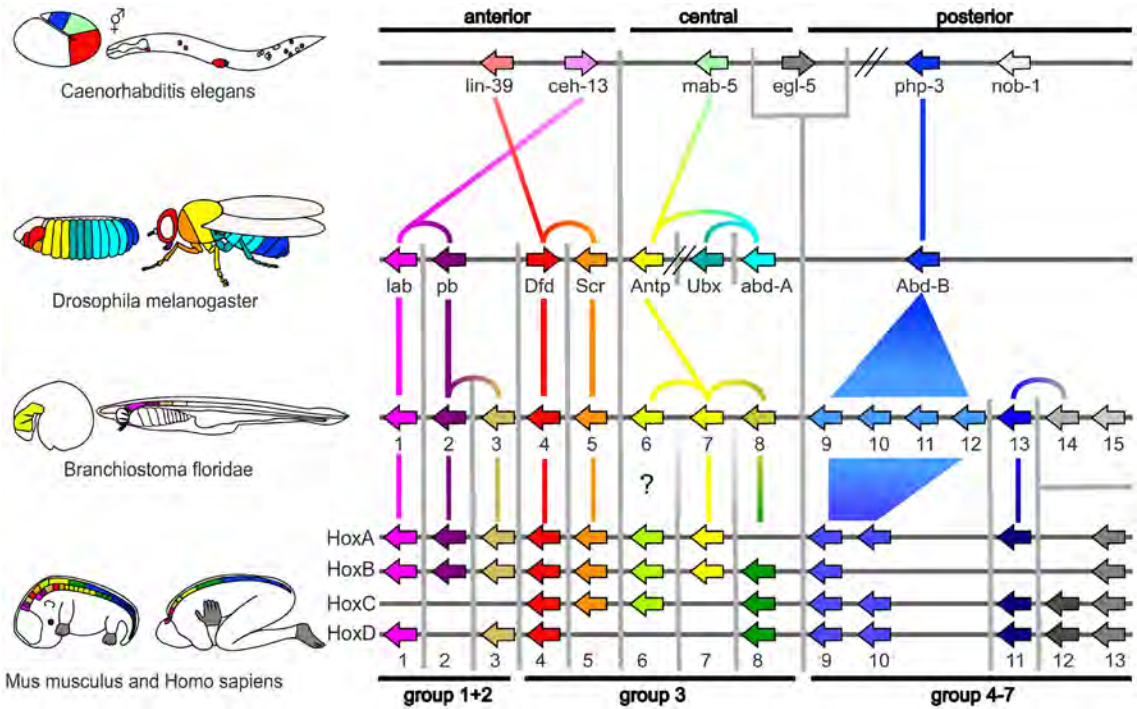


Figure 2.14.
The hox cluster located within the homeobox genes within the DNA is highly preserved across different species throughout the evolutionary timeline. Through the hox cluster, and the role it plays in defining which body part grows in which part of the body, species are able to vastly differ morphologically through the same genetic processes.

2.3.5. Evo-Devo and The Modern Synthesis

The genetic role of mutations on the development of an organism is crucial for the understanding of evolution. However, at the time the modern synthesis was drawn up in the 1940s, the role of genes on the development and evolution of form was yet to be discovered (Carroll, 2008). Although Julian Huxley briefly stated that "...a study of the effects of genes during development is as essential for an understanding of evolution as are the study of mutation and that of selection" (Huxley, 1943). Gilbert, Opitz and Raff (1996) clarify that the role that embryology and developmental genetics played in the modern synthesis was non-existent. However, it was during the discovery of the homeobox in the early 1980s that cemented the significance of the role of developmental biology in evolution.

The principles of evolutionary developmental biology (evo-devo) conflict with some of the principles of the modern synthesis. Where the original conclusions of the modern synthesis stated that the origins of novelty and the great diversification of phenotypes were attributed to gene duplication or the evolution of proteins in the DNA, the studies of evo-devo attribute the vast morphological diversity of phenotypes to gene regulation, regulatory networks and regulatory sequences in the genome (Carroll et al., 2005). Although gene duplication continues to play a role in phenotypic diversity, the studies of evo-devo clarify that it is a much smaller one than previously assumed. The discoveries of evo-devo were not novel to the evolutionary field; in 1975, before the discovery of the homeobox, King and Wilson attempted to explain the challenge of "how species which have such substantially similar genes can differ so substantially in anatomy" (King and Wilson, 1975, p. 107) by suggesting that anatomical evolution was more of the result of changing gene regulation than that of the changing of protein sequences.

Gerd Muller (2007) clarifies that the genetic advances in evolutionary development attributed changes in the phenotype as the result of alterations in developmental mechanisms rather than the result of statistical gene frequencies in populations. The alteration of developmental mechanisms in the genome address several aspects of phenotypic change, such as the "generation of new structural elements (novelty), the establishment of standardised building units (modularity, homology), the arrangement of such units in lineage-specific combinations (body plans), and the repeated generation of similar forms in independent taxa (homoplasy)" (Müller, 2007, p. 946). Further substantiating the ascription of phenotypic variation to mutations in the regulatory regions of the DNA rather than gene duplication.

It must be clarified that evo-devo is not a science that attempts to replace the principles established in the modern synthesis, but simply attempts to add another level of explanation. As Carroll states, "There can be no doubt that if the facts and insights of evo-devo were available to Huxley, embryology would have been a corner stone of his modern synthesis, and so evo-devo is today a key element of a more complete, expanded evolutionary synthesis" (Carroll, 2008, p. 34).

2.4. Computation

2.4.1. Optimisation Methods

The algorithmic translation of biological evolutionary principles as optimisation methods form a significant part of the computer science literature. Variant algorithms and methods include the Genetic Algorithm, Evolutionary Programming, Evolutionary Strategies, Ant Colony Optimisation, Particle Swarm Optimisation, Genetic Programming and Differential Evolution. However, optimisation techniques are not limited to those derived only from the biological paradigm; there exists in the field several alternative optimisation methods that aim to find the fittest solution for an optimisation problem through approaches that are not derivative from the natural world. Hill climbing, Simulated Annealing, Tabu Search, Direct Search, Random Optimisation and Gradient Based Optimisation are examples of such alternative methods (Luke, 2013; Cavazzuti, 2013; Weise, 2009). However, there is a paradox with the term 'optimisation' and its relevance in the natural world. It signifies that solutions reach an ideal or perfect state in response to environmental conditions; whereas in natural systems, there is no ideal or perfect solution, rather solutions that are simply well adapted to their environmental context. John Maynard Smith addresses these issues, and clarifies that optimisation theory and its relevance in biology "is not to demonstrate that organisms optimise. Rather, they are an attempt to understand the diversity of life" (Smith, 1978, p. 122) and further clarifies that the applicability of optimisation carries with it several assumptions, primarily being the phenotype set and its characteristics; the fitness objectives being optimised for and finally, the population structure and the methods related to how features are inherited between generations. (Section 2.4.2 further discusses the relationship between optimisation and adaptation in the literature).

There lies the incorrect (and generalised) assumption that evolutionary based algorithms are the most efficient optimisation algorithms in the field; (research by (Wortmann et al., 2017; Weise, 2017; Weise et al., 2016; Wetter and Wright, 2004) have challenged this assumption); which may be partly due to the recent surge in their popularity. In reality, there is no one 'perfect' optimisation method or algorithm. The optimisation method being applied is highly dependent on several factors such as the complexity of the design problem, the size of the problem, the time available to run the optimisation algorithm, the number of objectives being optimised for and whether the optimal solution is required or a near optimal solution is sufficient (Burke, 2014; Cavazzuti, 2013; Rothlauf, 2011; Weise, 2009; Miettinen, 2008). Additionally, there are examples of optimisation algorithms that hybridise different methods, in an attempt to take advantage of multiple optimisation concepts within the same algorithm (Mladineo et al., 2015; Hoseini and Shayesteh, 2013; Yoo and Harman, 2010; Kampf and Robinson, 2009; Keedwell and Khu, 2005; Chuanwen and Bompard, 2005; Shi et al., 1999; Ruan, 1997), however, these attempts are geared towards specific optimisation problems. Although there are attempts by scholars in the field to put forward optimisation algorithms that are more generalised and applicable towards a larger subset of optimisation problems (Seada and Deb, 2015), a single 'perfect' optimisation method cannot be assumed to exist as each optimisation problem is unique to its own framework.

In the context of the presented research, and within the framework of the conducted experiments addressing multiple objectives and a large search space, an evolutionary algorithm will be used to run the evolutionary simulations. Although research by (Wortmann et al., 2017) demonstrates that EAs may not be the most efficient optimisation method for single objective problems; within the framework of the conducted experiments of this thesis addressing multiple objectives and a large search space, an evolutionary algorithm remains the preferred optimisation method (Luke, 2013; Rothlauf, 2011; Deb, 2008; Branke et al., 2008, Coello, 2006) as evolutionary based optimisers “(i) do not require any derivative information (ii) are relatively simple to implement (iii) are flexible and have a wide-spread applicability” (Deb, 2008, p.60), and when compared to mathematical programming techniques that tackle multi-objective problems, evolutionary algorithms are “less susceptible to the shape or continuity of the pareto front” and do not “require differentiability of the objective functions and the constraints” (Coello, 2006, p.29). More importantly however, as discussed in **Section 1.5.**, the objective of the computational applications in the presented thesis is to focus primarily on the processes that sit at either end of the optimisation algorithm and less so on the algorithm itself; the aim is to highlight the significance of these processes on ensuring the optimisation algorithm is utilised efficiently and to its full potential.

2.4.2. Algorithmic Application of Evolutionary Principles

Evolutionary Algorithms have been used extensively in recent years to mimic the principles of evolutionary science to solve common real-world problems through search and optimisation procedures of single or multiple objectives. Ranging from the fields of economics to politics and music to architecture, evolutionary algorithms have proven to be an efficient problem-solving technique to find multiple trade-off solutions for problems that possess multiple ‘fitness criteria’ (objectives) that are in conflict with one another.

In its simplest form, an evolutionary model is best described as a two-step process of random variation within the genome of a phenotype, and the selection of said phenotype through environmental pressures (Mayr, 1988). This forms the basis of most evolutionary algorithms such as the NSGA-II algorithm (Deb et al., 2000) and the SPEA-2 algorithm (Zitzler et al., 2001) in which the developed algorithmic setup is formulated through the basic looped process of generating an initial population of competing random solutions, modifying the solutions through random variations, evaluating the solutions through an objective performance measure, and finally, selecting some solutions while discarding others through a predefined selection mechanism (Fogel, 2008).

Although evolutionary algorithms are derived from evolutionary principles, the algorithmic process by which a population of individuals ‘evolve’ towards a local or global optimum may be viewed as a teleological process that is driven towards an end goal. There is yet to be a consensus to justify this fundamental difference between the algorithm and its biological counterpart; some authors in the field attribute it as a “change in semantics” (Weise, 2009, p. 48), while

others outline the process of evolutionary algorithms as one that is similar to the “selective breeding programs of animals and plants” (Paterson, 2002, p. 5), rather than one that attempts to evolve new species or employ natural selection (Paterson, 2002). However, De Jong (2006) argues that if an evolutionary system is viewed as a “complex, adaptive system that changes its makeup and its responses over time as it interacts with a dynamically changing landscape,” then an evolutionary algorithm is represented as a “feedback control mechanism responsible for maintaining some sort of system stasis in the face of change” (De Jong, 2006, p. 23). Therefore, when comparing the local optimum in an evolutionary algorithm to a biological evolutionary process, Weise (2009) argues that achieving the local optimum in an evolutionary algorithm corresponds to a “well-adapted species that dominates all other animals in its surroundings” (Weise, 2009, p. 3).

Nevertheless, several applications of an evolutionary model as a computational process have been developed throughout the mid-20th century; the most prominent of these algorithms were Rechenberg and Schwefel’s ‘evolutionary strategies’ (Rechenberg, 1965), Fogel’s ‘evolutionary programming’ (Fogel et al., 1966) and Holland’s ‘genetic algorithm’ (Holland, 1962) (De Jong, 2006). Although each of these models have been founded and developed almost independent from one another, the establishment of several evolutionary algorithm (EA) conferences in the 1990s resulted in highly beneficial interactions between the domains of evolutionary computation. De Jong (2006) clarifies that “the result of these first interactions was a better understanding of the similarities and differences of the various paradigms, a broadening of the perspectives of the various viewpoints, and a feeling that, in order to continue to develop, the field as a whole needed to adopt a unified view of these evolutionary problem solvers”.

The ‘integration’ of different evolutionary paradigms, and the challenge associated with finding a solution to multiple conflicting objectives, led to a surge in different evolutionary algorithms. Each employed a different evolutionary strategy driven by a different interpretation of evolutionary principles with the ultimate objective of achieving the most optimal solution-set to a problem in an efficient timeframe. However, the two basic evolutionary principles of selection and variation remain the main driving force behind most evolutionary algorithms. Zitzler (1999) explains that “In evolutionary algorithms, natural selection is simulated by a stochastic selection process. Each solution is given a chance to reproduce a certain number of times, dependent on their quality. Thereby, quality is assessed by evaluating the individuals and assigning them scalar fitness values. The other principle, variation, imitates natural capability of creating “new” living beings by means of recombination and mutation.”

The development of different evolutionary strategies over the past few decades has revolved around the efficiency of an algorithm to apply these two basic principles in order to achieve the two most fundamental objectives of multi-objective optimisation (Zitzler et al., 2001):

- Application of the most efficient assessment and selection methods to achieve the optimal set of trade-off solutions – the Pareto optimal set.
- Maintain a diverse population throughout the simulation run in order to minimise the probability of premature convergence and maintain a dispersed Pareto optimal set.

Thus, the methods by which different evolutionary strategies apply the principles of selection and variation are notably diverse in different evolutionary algorithms. However, the most progressive evolutionary algorithms (e.g. NSGA-2, SPEA-2) excelled through their ability to achieve the most diverse Pareto optimal set in both an efficient timeframe and a within a reasonable computational environment (Luke, 2013).

Although the algorithm mimics natural evolution by incorporating variation and selection strategies to evolve the population towards an optimal solution set, the intensity of their application is essential in generating a diverse solution set within an efficient timeframe. Ideally, the algorithm setup should balance a search and optimisation strategy that is both explorative – in which it employs an adequate degree of mutation and crossover to allow for a diverse population of candidate solutions; as well as exploitative – where an efficient selection and variation strategy directs the algorithm towards an optimal solution set within a feasible number of generations (Luke, 2013).

However, the foundations of genetic algorithms have been significantly contingent on the principles of evolution established in the modern synthesis in the 1940s. Although genetic algorithms apply key principles of an evolutionary model to computation problem solving, these principles reflect phenotypic variations through statistical gene frequencies in populations. However, the mutation of gene regulation and regulatory sequences in developmental biology and their effect on the evolutionary process of organisms is severely lacking in genetic algorithms. The discoveries in developmental biology have greatly challenged the principles established in the modern synthesis, these discoveries are yet to manifest themselves in genetic algorithms, thus resulting in an incomplete translation of how evolution functions on the genetic level and consequently an incomplete portrayal of a biological evolutionary model through evolutionary computation. Nonetheless, the significance of the application of an evolutionary biological model computationally in different fields of research has manifested itself to be a valuable and advantageous endeavour.

2.4.3. Principles of Evolutionary Algorithms

Most evolutionary algorithms share the same central algorithmic setup, although most recent algorithms have contributed significantly to this setup and have modified it in an attempt to generate a more efficient algorithm, the 4-step iterative process detailed below is common to most algorithms (Luke, 2013; De Jong, 2006; Back et al., 1997; De Jong et al., 1997; Fogel, 1997) (figure 2.15.).

1. The algorithm starts by generating an initial population (this initial population can be random or pre-determined); the objective of this initial population is to provide the evolutionary process with a 'start point'. In the experiments conducted throughout this research, this initial population is always created randomly; this was done to ensure that user preference played no role in directing the algorithm towards a predefined solution set.
2. According to predefined probability percentages, randomly selected individuals within this population are randomly modified. This is conducted through a 2-step process:
 - a. The first step is by means of a *breeding* operation, in which the *genotypes* of different individuals *cross-over* with one another through predefined breeding mechanisms (such as using 1-point crossover, 2-point crossover or uniform crossover).
 - b. The second step creates variants (*mutations*) within the *genotype* of each individual. Also, according to the predefined probability percentage, a number of individuals are selected and their genotypes are modified; the intensity of the variants is predefined, as is the type of variant.
3. Each individual in the population is evaluated according to predefined fitness functions and attributed with a performance measure. It is crucial that each solution is *numerically* measured as the individual's performance measure will be used to determine the individual's rank within the population.
4. According to a predefined selection strategy that is driven by the ranking of the individuals within the population; individuals will be selected to continue for next generations, while other individuals will be ignored and not allowed to continue in the simulation as they will have been deemed to be too weak to continue.

The process outlined above formulates the foundation of most (if not all) evolutionary algorithms, after step 4, the process loops and repeats steps 2 to 4 until a limit is reached. This limit can vary from being a time limit predefined by the user, or a generational limit (how many generations does the user want the simulation to run), or in more advanced simulations, a limit defined by the algorithm itself (for example *if* the algorithm converges towards a specific solution set, then *end* the simulation).

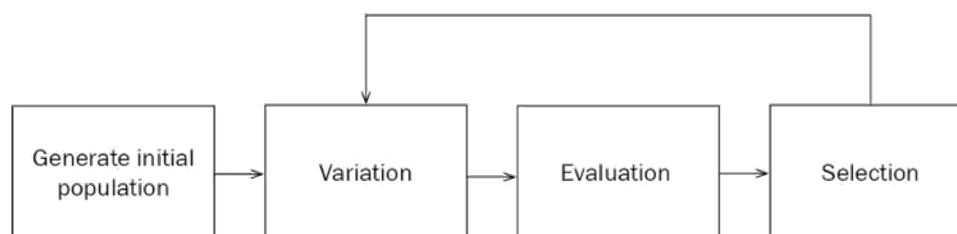


Figure 2.15.
The Evolutionary Algorithm:
The algorithmic loop that
forms the foundation of most
evolutionary algorithms
developed.

2.4.4. Multi Objective Evolutionary Algorithms

The difference between multi objective evolutionary algorithms (MOEAs) and single objective evolutionary algorithms (SOEAs) is relatively straight forward; the former applies an evolutionary problem solving approach for problems that are constructed from multiple (usually conflicting) objectives, while the latter utilises the same (or similar) evolutionary approach for problems with single objectives (or problems with multiple objectives that don't conflict, thus allowing the user to combine the objectives into a single composite function before running the algorithm). More importantly, SOEAs provide the user with a *single* solution to the problem being investigated; because the problem is comprised from one objective, it is naturally understood that the problem is solved through one solution – the most optimal solution. However, due to MOEAs comprising from *multiple conflicting* objectives, there can be no *single* optimal solution, as an optimal solution for one objective may be an underperforming solution for another objective, therefore the output of a MOEA is set of solutions that attempt to optimise for each objective *independently* within the same algorithmic run (Deb, 2006). In evolutionary computation, this set of optimal solutions is usually referred to as the *Pareto Optimal Solutions*, and they comprise the *Pareto Optimal Front* (described in detail in the following sections).

Evolutionary multi-objective optimisation has been extensively applied as a problem-solving strategy since the late 20th century; Although the earliest applications of evolutionary principles as an optimisation process date back to the 1930s, through the work of Sewall Wright (1932), and then later more forcefully through the work of Holland's genetic algorithm (GA) (Holland, 1962), Rechenberg and Schwefel's evolutionary strategies (ES) (Rechenberg, 1965) and Fogel's evolutionary programming (EP) (Fogel et al., 1966); it was not until the 1980s that the first attempts to design a multi-objective evolutionary algorithm (MOEA) emerged, primarily through the work of David Schaffer's 'Vector Evaluated Genetic Algorithm' (VEGA) (Fonseca and Fleming, 1995; Schaffer, 1984) where a population of individuals were selected between generations opposed to the conventional approach of single-objective evolutionary algorithms (SOEA) in which a single individual was selected to create subsequent generations.

One of the seminal figures in the field of MOEA, David Goldberg, put forward the concept of integrating pareto optimality and dominance as a selection strategy within an evolutionary algorithm, allowing for the algorithm to incrementally increase the fitness of the solutions for each fitness criteria independently yet avoid early convergence towards a local optimal solution (Goldberg, 1989). Inspired by Goldberg's research, many of the leading MOEAs of the 1990s incorporated his selection strategies, most famous were the Multi-Objective Genetic Algorithm (MOGA) (Fonseca and Fleming, 1993), Niched-Pareto Genetic Algorithm (Horn et al., 1994) and the Non-Dominated Sorting Genetic Algorithm (NSGA) (Srinivas and Deb, 1994).

The early 21st century witnessed a major development in MOEAs through the introduction of the Elitism Strategy, a concept primarily credited to Eckart Zitzler through his algorithm titled Strength-Pareto Evolutionary Algorithm (SPEA) (Zitzler, 1999) (the SPEA was developed into a

second more robust algorithm titled SPEA-2 (Zitzler et al., 2001) (figure 2.16.)). The objective of utilising an elitism strategy (or what is sometimes called an Archive) within MOEAs is to allow non-dominated solutions to compete with individuals that lie outside of their respective generations. Zitzler's concern was that although a non-dominated solution may have earned its non-dominated status within its own generation, it may also be non-dominated across multiple generations, however by not allowing it to 'survive' in order to compete with future generations, the solver may lose potentially highly fit individuals, therefore the elite were the solutions that were preserved across multiple generations and only replaced by fitter non-dominated solutions (Zitzler, 1999). Zitzler's SPEA inspired other MOEAs to incorporate the elitism strategy, most notably Knowles and Corne's Pareto-Archived Evolution Strategy (PAES) (Knowles and Corne, 2000) and Kalyanmoy Deb's second attempt at his NSGA algorithm titled NSGA II (Deb et al., 2000).

Although many of the MOEAs have advanced dramatically over the last decade (the NSGA III for example can now handle problems with 20 objectives while current research aims to increase this number to 100 (Deb, 2017)), the comparison between these algorithms is contingent on the algorithms' ability to reach optimality of its solutions yet simultaneously maintain their diversity. This issue becomes highly significant when the variation of the solution set reflects phenotypic diversity within the population, primarily in cases where the formal and geometric attributes of the generated solutions are the required result. Therefore, variation and diversity within a generation – and between generations – is essential to users implementing MOEAs for geometric solutions; more importantly however, dynamically controlling variation throughout the simulation run, and gaining access to the full historic record of all solutions within the population is essential when the result required is a set of solutions; a set that is selected based on criteria that are independent from the objectives that run the algorithm.

The significance of this relates to the early challenges faced by non-population based MOEAs of the 1960s, where the user had to apply their weighting preference to the objectives at the end of every generation (by being forced to select one solution to carry on to the next generation); one of the earliest examples of such attempts was in the work by Rosenberg (1967). Although population based MOEAs have bypassed this condition, they have not foregone it, rather simply delayed it from being applied at the end of every generation to having to be applied at the end of the simulation. However, the question remains, what are the criteria to which the user selects the final – or final set – of solutions? Thus, to limit the user's subjective preference when selecting the solutions, the independent selection criteria mentioned in the paragraph above provides the user with an statistical and informed approach to selecting the final solution set (Deb, 2006).

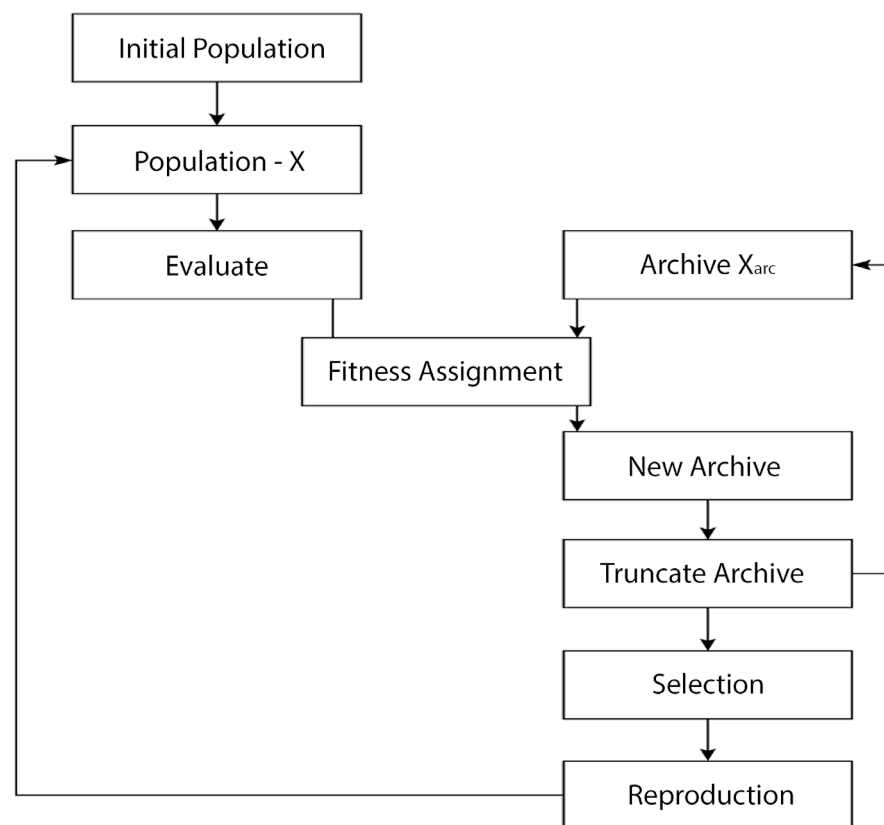


Figure 2.16.
The Strength Pareto
Evolutionary Algorithm 2:
The SPEA2 written by Eckart
Zitzler uses the Archive to
allow solutions from older
generations to compete with
solutions created in the latest
generation (Zitzler et al.,
2001).

2.4.5. Evolutionary Processes in Design

In design, the application of evolutionary processes has been additionally beneficial as the *phenotype* in design is key. More importantly however, many design problems are inherently multi-objective as they usually have multiple end users, thus requiring a process that removes the designer's subjectivity in favour for objectively addressing the end user's requirements. The advantages and applications of biological evolutionary processes as models for design have been seen through the work of several architects/planners throughout the second half of the 20th century (Batty, 2013; Coates, 2010; Weinstock, 2010; Marshall, 2008; Frazer, 1995; Steadman, 1979) (figure 2.17.). However, the role of computation in generating an efficient iterative process has been one of the primary advantages for the application of an evolutionary model in design. Frazer (1995, p. 10) states that "the computer can be used not as an aid to design in the usual sense, but as an evolutionary accelerator and a generative force". Moreover, the integration of evolutionary algorithms within some of the most widely used computational modelling software has made designers' access to the application of evolutionary processes as design models more streamlined than in any other point in history.

Due to the nature of the computational application of an evolutionary model, their emergence within 3d modelling software was coupled to the development of highly integrative and user-friendly plugins that equipped the user with a streamlined approach to generative and algorithmic modelling. Although most 3d modelling software had integrated within them the capability to model through code, in which an iterative process could be developed (for example, VB Script in Rhino 3D, melScript in Maya), these required highly detailed knowledge of writing in code, and although some users took on this task, the majority did not. It was not until Grasshopper3D was developed that allowed users to comfortably approach algorithmic modelling as it provided them with an object-based user interface rather than a textual one. The developer of Grasshopper3D, David Rutten states (Rutten, 2013) that "GH (*grasshopper*) was developed for Rhino users as a way to automate tasks without the need to write textual code". Although this instigated a change in how designers approach 3d modelling, it also provided an optimal platform for developers to create a user-friendly approach for the application of evolutionary processes in design that did not necessitate the user learning code or writing their own evolutionary algorithms.

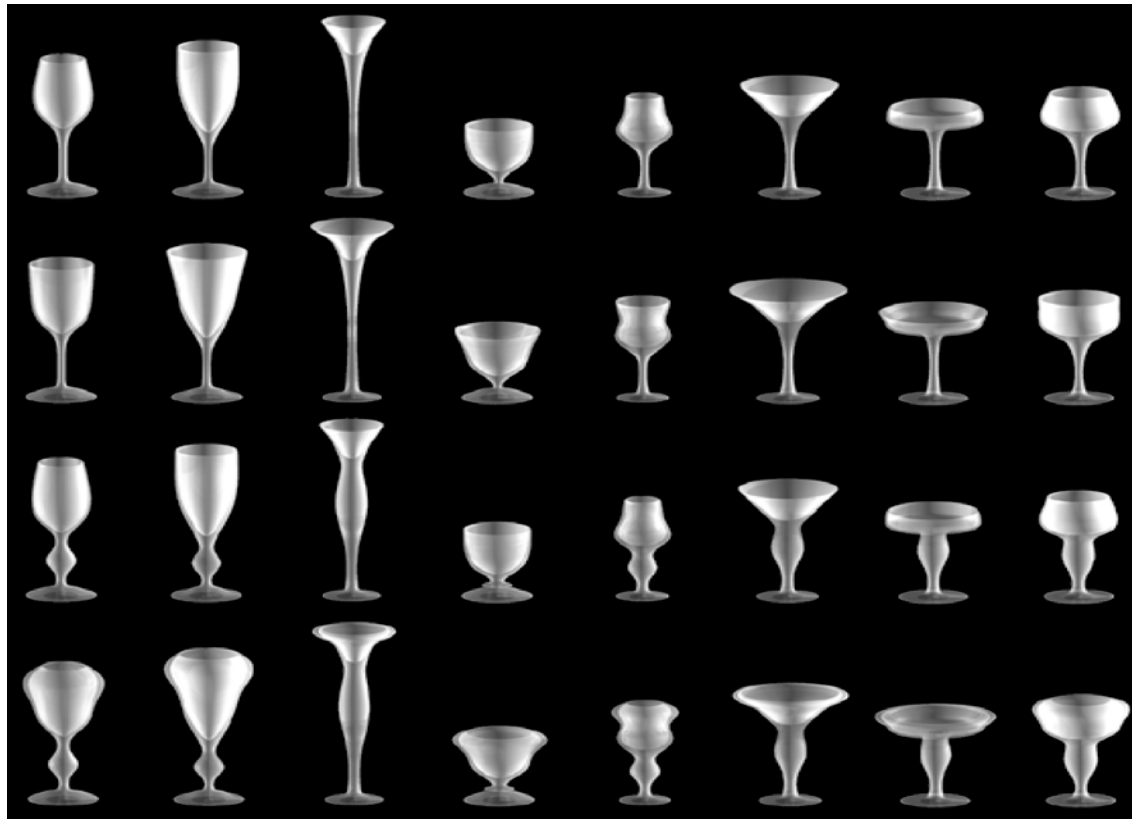


Figure 2.17.
*Evolutionary Computation
in Design: The application of
evolutionary algorithms for
the design of a population
of wine glasses (Hung et al.,
2001).*

2.4.6. Evolutionary Solvers in Design

One of the first evolutionary solvers (if not the first) to be released within the Grasshopper3D framework is the solver called *Galapagos* developed by the author of Grasshopper3D David Rutten in 2010 (Rutten, 2010). Although a robust tool, Galapagos was a single objective evolutionary solver, and for the purposes of the conducted research, which tackled multi-objective design problems, was not utilised. However, being the first to put forward an evolutionary solver within grasshopper3D, this provided other developers with the necessary libraries and framework to develop their own solvers. Three of which are Octopus (Vierlinger, 2013a), Biomorpher (Harding and Branst, 2017) and Design Space Exploration (MIT, 2017); Although all multi-objective, each solver approaches evolutionary design modelling differently, the three solvers are outlined below:

Biomorpher

Developed by John Harding and Cecilie Brandt in 2016 (Harding, 2016), the plugin employs an *interactive* approach to generating design solutions for a design problem. A significant drawback of this approach is that it requires the user to make a decision at every iteration of the algorithm, in which the user must *select* which solutions will breed and form the consequent generation. This defies the purpose of many MOEAs, which are employed to *remove* user preference from the design process allowing the user with an objective approach to the design problem. The development of MOEAs was the result of the user having *too much* control over which solutions are fit and which are not; in conventional non population based MOEAs, the user had to select one parent from each generation to create the next generation, the problem with this is that at the end of each generation, the user had to make trade-off decisions for which individual they thought were the most optimal, this has caused the user to influence the simulation significantly (Deb, 2001). The selection process in *Biomorpher* seems to be an extension of this. Even though the user can select several parents (and so, the user can choose to select parents that are conflicting), the fact that choice is allowed at the end of *every* generation will very likely lead to the user influencing and directing the simulation with their own personal preference, rather than allowing the simulation to optimise for each objective independently.

Additionally, through employing a user-based selection approach, *Biomorpher* bypasses the 'archive' (or elitism) method; in which solutions are sorted according to how they perform (numerically) when compared to all other solutions in the generation. More importantly, one of the significant benefits of the archive is that it allows for solutions to *compete* and be measured against solutions from outside the current generation, this ensures that solutions that were deemed to be fit are not lost and continue to survive throughout the population (Knowles and Corne, 2000). In addition to the above, the plugin does not provide a clear indication of what the mutation and crossover operators are, nor does it allow the user to modify the intensity of these operators which would help control levels of exploration and/or exploitation throughout the fitness landscape.

Design Space Exploration

Developed by Digital Structures at MIT, Design Space Exploration (DSE) utilises the NSGA-2, a Multi-objective evolutionary algorithm developed by Deb et al. (2000), in which it utilises an elitist approach that sorts solutions based on dominance. The plugin gives significance to the pareto front, however, without the application of the hypervolume indicator (or similar measures), in complex design problems, the pareto front is comprised from all of the solutions in the final generation, thus reducing its significance in assisting the user with selection. Moreover, DSE does not integrate within it a *mesh* input which in turn would output the corresponding meshes for the solutions generated in the population.

Although a robust plugin, DSE is less visual in its analysis of the algorithmic run, as its outputs are numerical data that require the user to extract and use as inputs for graphical visualisation. The downside of this approach is that the solver does not output data iteratively, the user must wait until the solver completes its run before gaining access to any data that would assist them in analysing the generated solutions. Alternative solvers (such as Octopus) provide graphical representations of the objective space and convergence graphs that are updated iteratively with the generation of each solution; this allows the user to make quick tests and changes to the design problem without having to run the entirety of the simulation. Despite this, DSE provides the user with the genome of each solution, which can be used to conduct further analysis on emergent patterns of different genes (and the associated morphological traits) throughout the population.

Octopus

One of the most widely used (and the least updated) evolutionary solvers within grasshopper3D is Octopus. The plugin was initially developed by Robert Vierlinger through his thesis titled *Multi Objective Design Interface* (Vierlinger, 2013b) and was later released in collaboration with Bollinger+Grohmann Engineers (Vierlinger, 2013a). The solver employs the SPEA-2 algorithm (Zitzler et al., 2001) which uses an elitist approach to multi objective problem solving. The solver integrates mutation strategies developed through the HypE algorithm (Bader and Zitzler, 2011) in addition to the incorporation of the hypervolume indicator (Zitzler et al., 2007), which addresses challenges of MOEAs ranking dominance amongst the population when the problem increases in difficulty (although this was applied in the plugin, it did not develop beyond beta mode).

Through Octopus, users are able to apply the SPEA-2 algorithm on any design problem they have created in Grasshopper3D, more importantly, Octopus's strength was in its output of the numerical data associated with each solution generated in the algorithm. Although the output was limited to the fitness measures for each solution, this nonetheless gave the user the ability to use this data to further analyse the results of the simulation. In addition to this, the user interface of Octopus equipped the user with graphical information – through convergence graphs and the objective space – that assisted them in recognising whether the design problem and solver settings created a highly exploitative (premature convergence) or highly explorative (too much

variation) fitness landscape (a significant drawback of this is that Octopus remaps the graphs to the most recent generation(s); by doing so, the user is not provided with a full account of the simulation's timeline). Similar to Galapagos, (but in more detail), Octopus aimed in educating the user with the different methods of using evolutionary algorithms by moving away from a 'black box' application of the solver, thus providing the user with enough information (however limited it may be) to analyse and modify their design problem for a more efficient algorithmic application. This was addressed in the plugin *Octopus.Explicit* (released by the same author), in which the user was provided with a 'broken down' solver that allowed them to modify parts of the algorithm without having to change any of the code.

Although interesting in its visual application of an evolutionary process in generating design solutions, Biomorpher gives greater significance to the users' visual preference rather than equipping the user with the necessary tools to better understand the inner workings of evolutionary algorithms, thus applying them to their maximum capability. Although there are significant similarities between Octopus and DSE, they far outweigh the performance of Biomorpher for the application of an evolutionary model to address complex design solutions. However, when comparing Octopus to DSE, both employ leading MOEAs that have been proven to perform significantly well on multi objective problems (Luke, 2013); therefore, their comparison is through the efficiency and clarity of information provided to the user. In this regard, Octopus outperforms DSE as it equips the user with a stronger graphical representation of the solutions, allowing the user to detect patterns early on in the simulation, thus taking measures to address their occurrence. This strengthens the users' ability to generate numerically driven morphological variation within the population more efficiently and provides the user with the data necessary to conduct further analysis on the generated solutions. Therefore, the experiments conducted throughout the presented research employs *Octopus* and *Octopus.Explicit* as the main evolutionary solvers.

Statistical Analysis of Evolutionary Algorithms

3.1. Introduction

The application of evolutionary algorithms in design is an incredibly robust tool, however, if used without adequate knowledge about its driving mechanisms and requisite 'set up', there is a significant risk of placing too much trust in the algorithm itself without giving the attention required to ensuring the experiment setup, and by consequence, the design problem, is properly formulated. In doing so, there is a high likelihood for either of the following scenarios to occur:

1. The evolutionary simulation will be unsuccessful in finding acceptable solutions for the design problem (this is usually followed by the incorrect assumption that the algorithm 'doesn't work').
2. Solutions are selected visually, which will require that only a small pool of solutions is analysed, by consequence arbitrarily dismissing the larger population set which may contain fitter solutions.
3. The design problem is so complex that the algorithmic run is very slow, in this scenario, a shorter simulation is performed in which the incorrect assumption is made that the data generated has been optimised; when in reality, the simulation did not have the adequate time necessary to efficiently explore the fitness landscape and converge towards a global (or high local) optima.

Therefore, a successful evolutionary simulation in design is driven by how well the design problem is defined (this does not imply that by doing so, any evolutionary algorithm can be used; one must also be critical of which algorithm is applied and why the selected algorithm is the most suitable to address the design problem). However, in defining a well formulated design problem lies a paradox; in order for user to confirm that the design problem is well formulated, he/she must first run the algorithm and analyse the results; this analysis is then used as a feedback mechanism to inform and modify the design problem. To address this, two factors are key when running an evolutionary simulation in design:

1. The user must run the evolutionary solver a minimum of two times, to ensure that the first set of results are used to modify and reformulate the design problem (at times, the solver must be run multiple times to ensure the design problem is efficiently expressed). As in all the natural sciences, to efficiently design the problem, the process must first be observed.
2. The mode of analysis of the outputted data by the evolutionary algorithm is key, as this will serve two primary purposes:
 - a. It will assist the user in understanding the results of the algorithm, and thus identify the parts of the experiment set up (design problem) that need to be modified.
 - b. Once the user is confident that the experiment set up is well formulated, the analysis of the outputted data will assist the user in selecting the solution (or group of solutions) that best address the design problem.

The above is integral to a successful application of evolutionary computation in design. More importantly, it highlights the significance of conducting a thorough analysis of the results, and the efficiency of the employed analytic methods in ensuring a complete and comprehensive understanding of the algorithmic run is achieved. This is critical for an accurate and effective evolutionary simulation, and so its implementation lies at the core of the computational process. However, the significance of the above is seldom highlighted in most applications of evolutionary computation in design; in the rare cases that have conducted an analysis of the algorithm’s output, this was limited in both its mode of analysis as well as its application, in which only a selected portion of the generated results were analysed rather than its entirety. More importantly, the conducted analysis was used to inform and adjust the parameters driving the evolutionary simulation (such as mutation rates and archive sizes) instead of informing and reformulating the design problem. Although adjusting the former may have some impact on the evolutionary run, its effects are much less consequential when compared to the latter.

In this context, the research develops multiple analytic tools that are integrated within the same computational platform of the evolutionary solver (Rhino and Grasshopper3d) yet simultaneously lie outside the evolutionary algorithm. In doing so, the tools developed provide a comprehensive analysis of the data generated by the evolutionary simulation without interfering with the evolutionary process itself (figure 3.1.).

The objective of the toolset presented in the following sections, and their integration within the evolutionary process, is to emphasise the analysis of the population over that of the generation; in doing so, all individuals evolved through the evolutionary simulation play a role in reformulating the design problem towards one that is more efficiently expressed, and by consequence, driving the algorithm towards generating a fitter and more varied population. Additionally, the population wide analysis ensures that any of the evolved solutions may be selected as a final output of the simulation, thus allowing for more variation between the selected solutions.

For a comprehensive understanding of the tools developed and their application within the computational process, the terminology associated with multi-objective evolutionary algorithms must first be described. This is presented in the following table (the definitions correspond to their relevance within computation and therefore are not to be interpreted as the biological definitions of the terminology):

Term	Definition
Simulation	A single algorithmic run of the solver from start to finish.
Individual / Solution	A unit generated by the evolutionary simulation, represented by a genotype and phenotype, that comprises the population
Generation	A single iteration of the evolutionary algorithm
Population	All individuals generated by the evolutionary simulation across all generations
Gene	A single parameter that defines one part of an individual. In Grasshopper3D, this parameter is represented by a numeric slider
Genotype	All the genes that define a single solution. The genotype may be considered as the solution's 'blueprint' or DNA
Gene Pool	The unique genes used by the different solutions in the population
Phenotype	The formal (or otherwise) representation of the solution. The phenotype is the manifestation of the genotype.
Fitness Criteria / Fitness Objectives	The design objectives that will run the simulation, and to which the phenotypes will be evaluated
Fitness Value	The empirical performance measure attributed to each solution according to the evaluation results
Fitness Rank	The ranking of each solution within the population according to its fitness value
Pareto Front	The solutions that are non-dominated by another solution. i.e. a solution that cannot be improved without negatively affecting the rank of another solution.
Elite / Archive	The fittest solutions in all preceding generations that are preserved in order to compete with the fittest solutions in the latest generation
Mutation	A change in a gene (or group of genes) in a genotype.
Mutation Probability	The probability of a gene to mutate. This determines how many genes in a solutions genotype will mutate
Mutation Rate	Once the mutated genes are selected, this determines the intensity of how much each gene mutates
Crossover	Exchange of genes between two solutions
Crossover Rate	The number of genes exchanged between the two solutions

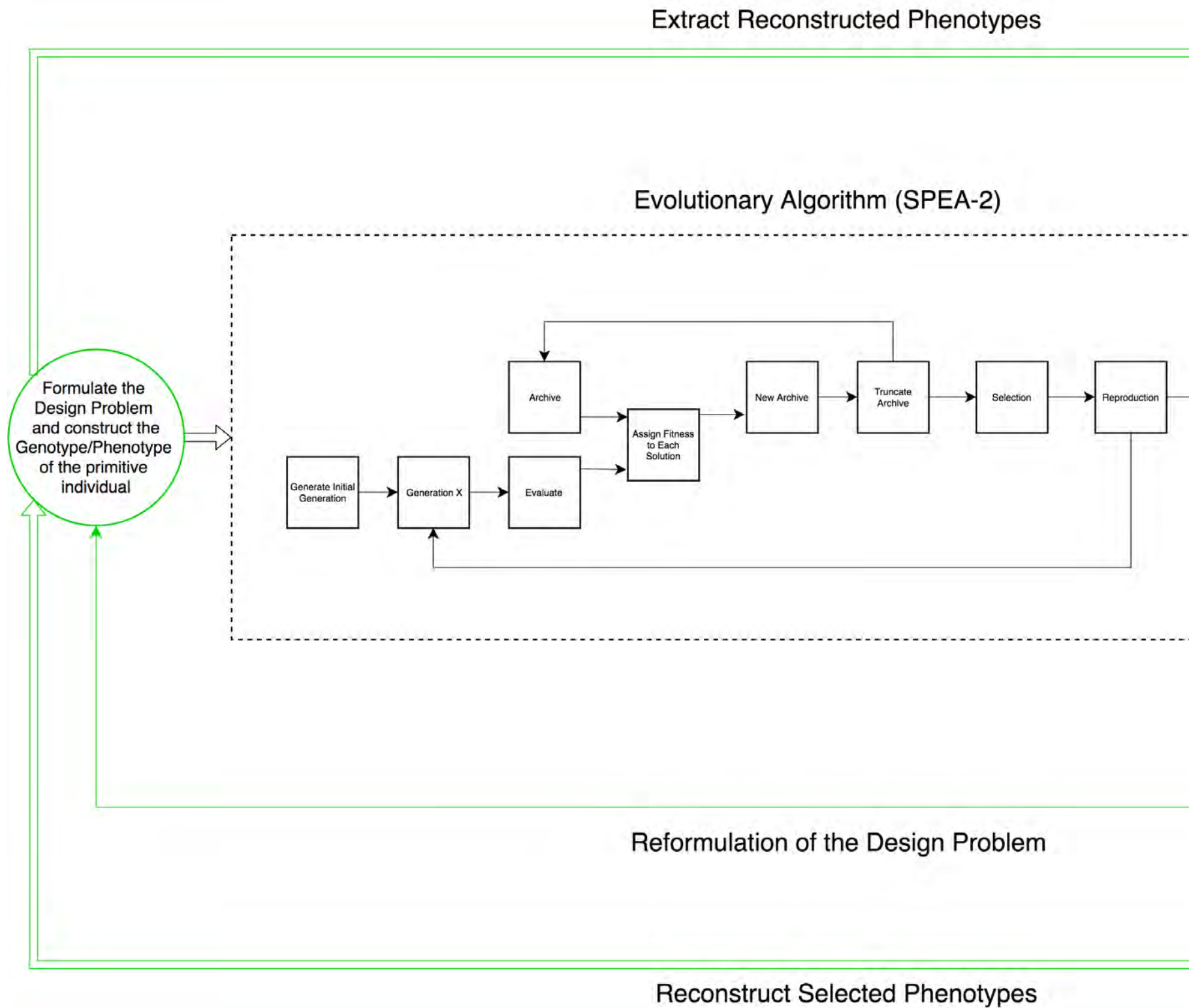
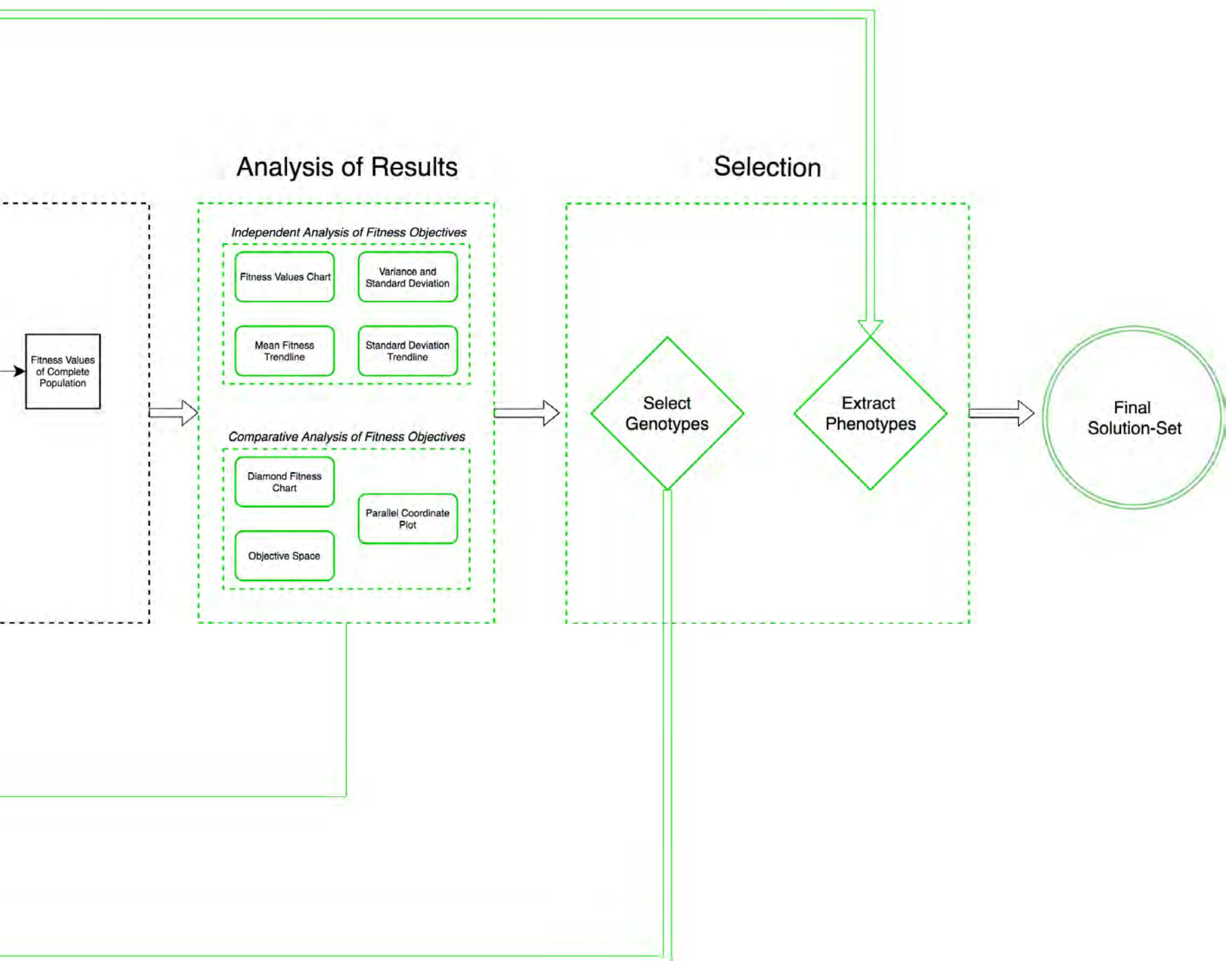


Figure 3.1.
Pseudo diagram presenting the workflow and relationship between the existing evolutionary algorithm (Zitzler et al., 2001) (black) and the tools and methods developed (green).



3.2. The Population

The inherent characteristic of an evolutionary algorithm is that it is an incremental repetitive loop, this means that in order for the algorithm to efficiently navigate the fitness landscape and converge towards an optimal peak (a group of fit solutions), it must make a small (random) change to the existing solution, analyse that 'changed' solution, and repeat the process (if the changed solution was fitter than the original solution, it repeats the process and moves in the same direction of the changed solution, however if the changed solution was less fit than the original, the algorithm repeats the process and moves in the opposite direction). As such, the robustness of the evolutionary algorithm lies with its ability to create a population of solutions, as it is through creating a population that the algorithm can explore different parts of the landscape simultaneously and optimise for different objectives independently within the same simulation run (Mitchell, 1998). In this context, the population is defined by how many individuals are in a single generation (generation size) multiplied by how many generations the algorithm runs before it is stopped (generation count).

$$\text{Population} = \text{Generation Size} : \text{Generation Count}$$

In design (as in other disciplines), the size of the population is dependent on the complexity of the problem. However, because the population is comprised from the generation size and generation count, attention must be given to the relationship between these two properties. As mentioned previously, in order for the simulation to navigate the fitness landscape, it must go through an iterative loop, and so in theory, the more loops the simulation goes through, the greater opportunity it will have in finding optimal solutions; in this case, the generation count takes precedence. However, if the generation size is too small, the algorithm will be working from a limited tool set, one that will not allow it to adequately explore the landscape, and in contrast, if too large, there is a high likelihood the algorithm will get 'lost' in the search space and not have the ability to converge towards an optimal peak. Therefore, although the population size is driven by the complexity of the design problem, the relationship between generation count and generation size is primary to ensure a successful evolutionary run. This signifies that one of the key characteristics of an evolutionary simulation is the population, and more importantly, that the size of the population must be primarily driven by the design problem. This means that a population may be comprised from 500 solutions (generation size = 20 : and generation count = 25) or from 10,000 solutions (generation size = 100 : generation count = 100).

3.3. Visual Analysis

In this context, the analytical methods employed for understanding the results outputted by the evolutionary simulation (the population) take centre stage. The first and most obvious analytical approach is that of the visual. Unlike other disciplines, the significance of the phenotype (the physical manifestation of the solution) in the design field is critical for the user, as it is the phenotype's morphological characteristics that define whether the selected design solution is successful or unsuccessful in addressing the design problem (this puts forward another challenge: how does the user define 'success', is it through visual analysis only or through some form of statistical analysis of the solution? This is addressed in the following sections). However, to visually analyse 10,000 solutions would be an almost impossible task (and would

defy the purpose of using the evolutionary algorithm in the first place). Therefore, to address this issue, users select a portion of the population in order to visually analyse a smaller solution set, in which the incorrect assumption is made that the final generation will by default hold the fittest solutions. Although this may be correct for single objective problems (or very simple multi objective problems), this is not the case for problems that are comprised from multiple conflicting objectives; as depending on the simulation, the final generation may be converged towards one (or some) of the objectives over the others and so would mean that fit solutions for the remaining objectives may be located elsewhere in the population's history (in older generations).

More importantly, to determine whether the evolutionary simulation was successful in generating a diverse set of optimal solutions, a full analysis of the entire simulation must be conducted. This allows the user to highlight anomalies within the population and identify emergent patterns that would have otherwise been undiscovered when analysing only a portion of the population. Through a comprehensive understanding of how the simulation behaves from one generation to the next (regardless of how many generations are in the population), the user can confidently make changes to the design problem in order to direct the simulation towards greater efficiency in its output. Moreover, due to the heuristic nature of the algorithmic application of an evolutionary process, the historical record of the population may contain solutions that exhibit traits that were unexpected by the user, yet beneficial in addressing the design problem. However, because the design problem was not properly formulated, the evolutionary simulation would have dismissed these solutions deeming them to be unfit. This signifies the necessity to analyse the full population rather than only a portion of it and use this analysis as a feedback mechanism to ensure the evolutionary algorithm is applied to its full advantage.

3.4. Statistical Analysis

An alternative approach to the visual evaluation of the solutions within the population is their statistical analysis. This is by far the more robust mode of analysis that is both efficient as well as highly informative to the user. By employing this method, it is no longer required to visually examine the morphological characteristics of each solution in the population in order to establish how well the simulation performed or whether emergent behaviour was observed throughout the simulation's timeline. More importantly, it takes full advantage of the numerical data associated with each solution; this is significant as it is this data that is the driving mechanism behind the algorithm. As such, and in contrast to the visual approach, the statistical model assesses the numerical data driving the algorithm rather than the morphological output generated by it.

This signifies the necessity for multiple simultaneous statistical analyses of the outputted data set; in which each mode of analysis highlights specific aspects of the simulation run which in turn provides the user with a comprehensive and detailed understanding of both the generated data and their evolution within the simulation. More importantly, the workflow behind how the data is analysed is crucial to ensure that the 4-step process of 1.) running the simulation, 2.) extracting the data, 3.) analysing the data and 4.) modifying the design problem is one that is as streamlined as possible. This ensures that whether the population size is 500 or 10,000, the analytical process and timeframe is the same. It is therefore essential for the user to be able to analyse a large data set and be provided with a visual representation that clearly reflects

the numerical data associated with each solution in the population. In doing so, the user is encouraged to set the population size in response to the complexity of the problem rather than the time required to analyse its outputted data.

The following section details the analytical modes developed, highlighting each tool's significance, workflow and benefits to the evolutionary process.

3.5. Analytic Tools

3.5.1. Understanding the Fitness Measure

To contextualise the following analytic toolset, an analysis of the fitness measure (or fitness value) and its significance to the evolutionary simulation must first be explained. The method by which an evolutionary algorithm optimises a solution is heavily dependent on how the solution is transcribed numerically. The numerical representation of a solution is defined as its fitness measure, and it is this measure that the algorithm optimises. In evolutionary algorithms, the solution is optimised by driving this numerical fitness measure towards 0 (in some evolutionary solvers, optimisation is through driving the fitness measure away from 0, this plays no role on the performance of the algorithm, it is a simple inverse function). If the solution's fitness measure reaches 0, it is then considered to have reached the most optimal state for the problem being solved. In design, the solution's fitness measure is related to the objective that the user intends to optimise for, this is best described through the following example:

Solution (phenotype):

Tower block

Design problem:

Design a block that receives as little solar gain as possible

Objective:

Minimise the solar exposure on the block's façade

Fitness Measure:

A numerical value that represents how much solar exposure is received by the block's façade

Variable (Gene):

Building Height

In the above example, the objective is to minimise the amount of solar exposure on the building façade, and so the algorithm will attempt to drive the fitness measure towards 0 (as mentioned previously, if the objective was to maximise the solution's fitness, then the fitness measure is inversed). The variable that the algorithm will modify in order to optimise the solution is the building's height. As this is a single objective problem, the algorithm will continue to modify

the building's height in the direction that creates fitter solutions, in this case, it will minimise the building height until the block's façade receives no solar gain. Given the design problem outlined above, coupled with the data inputted to the algorithm, the fittest (or most optimised) solution is when the block completely disappears, as by doing so, it no longer receives any solar gain. Although this is most likely not what was intended to happen, it is the only reasonable outcome according to how the design problem was formulated. Therefore, if the intention is for the building not to disappear, then the design problem requires revision to ensure that this does not occur. One way to achieve this is by limiting the variable to a specific domain, in which the algorithm is not allowed to make changes outside of the defined numeric range (for example, the height gene is limited to a minimum of 4 metres).

In the above example (and in single objective problems in general), the evolutionary algorithm is usually always capable of driving the fitness measure towards '0'; however, this is seldom the case in multiple conflicting objective problems, as by optimising one fitness measure towards 0, the second fitness measure is driven away from 0. An example of this is to modify the design problem above into the following:

Solution (phenotype):

Tower block

Design problem:

Design a block that receives as little solar gain as possible

Objective 1:

Minimise the solar exposure on the block's façade

Objective 1 Fitness Measure:

A numerical value that represents how much solar exposure is received by the block's façade

Objective 2:

Maximise the number of inhabitants in the building

Objective 2 Fitness Measure:

A numerical value that represents how many inhabitants reside in the building (density)

Variable (Gene):

Building Height

In response to the problem faced in the previous example, in which the building optimised by reducing its height to the minimum value (and thus disappearing), the design problem has been revised to address this issue through introducing a second objective that conflicts with the first. In

the revised design problem, the algorithm is required to minimise solar gain yet simultaneously maximise inhabitant density. However, by doing so (and considering only the information provided in the example above), the fittest solution for the solar gain objective (the building with the least height) is by consequence the least fit solution for the density objective (in this case, the fittest solution for the density objective would be the building with maximum height) and vice versa. This multi objective approach provides the user with multiple design solutions as there is no single optimal solution. Each solution generated by the algorithm possesses a fitness measure that is either optimal for one objective or the other (or the average, in which the solution is neither fit nor unfit to either objective). Although this introduces a second challenge of how to select between the solutions, it signifies the importance of the population as a design output rather than the single individual. In doing so, the variation exhibited between the solutions in the population is key.

3.5.2. Fitness Values

The above highlights the significance of the fitness measure in the evolutionary simulation, however it also signifies the importance of comparatively analysing each solution's fitness (or fitness value) throughout the entirety of the population. By doing so, the user is equipped with an adequate and comprehensive understanding of the algorithmic run and how efficiently the solutions evolved in response to the fitness objectives defined in the design problem. In this context, the first analytic tool is the "Fitness Value Chart". The graph plots each solution as a single 2-dimensional point, in which the X-axis value of the point is its location in the generation (for example, if the generation size is 50, the solutions are numbered from 0 to 49 accordingly), and the Y-axis value of the point is the solution's fitness value. The 2-dimensional points representing solutions within the same generation are connected through a single polyline to highlight whether there is a trend among the fitness values throughout the generation. Consequently, the polylines (i.e. the generations) are colour coded using a gradient from blue to red, where blue represents the oldest generation and red represents the latest generation. Through plotting all solutions and generations within a single chart, the user is able to assess the amount of variation of fitness values between the solutions of a single generation, and whether the overall fitness between the generations is improving (the polylines representing each generation moves towards the '0' point on the Y-axis as the simulation progresses), getting worst (the polylines move away from the '0' point on the Y-axis) or staying the same (the polylines fluctuate around the same Y-axis value). Moreover, the user can highlight any solution in the population, by specifying its location, to provide further insight on the performance of a specific solution compared to the population. The location of a solution in the population is determined as follows:

$$\text{Solution Location} = \text{Generation Number} / \text{Position in the Generation}$$

One of the drawbacks of the fitness value chart is that each fitness objective is analysed separately; although this provides the user with detailed insight on how the solutions for the analysed fitness objective are performing, there lacks a cross reference to the performance of the other fitness objective(s). Although this can be easily solved by analysing two (or more) of the objectives next to one another using multiple charts, several of the analytic tools developed (discussed in the following sections) provide the user with the ability to analyse all objectives within the population simultaneously (figure 3.2.).

3.5.3. Mean Fitness Value

The second tool is the comparative analysis of the mean fitness value for each generation within the population. The mean value for each generation is plotted as a 2-dimensional point, in which the X-axis value of the point is the generation number and the Y-axis value is the mean fitness value of the generation being plotted. This analytic approach does not give any preference to the mean fitness value itself, nor does it aim to provide the user with a solution in the generation (or population) that is considered to be average solution. As discussed in previous sections, this is against the populationists approach as by doing so, it would imply that the average solution may be considered as a representative of all solutions in the generation, which is not the case. What this analytical method does aim to achieve is a comparative analysis of the mean fitness value between the generations, thus highlighting the mean trendline throughout the population. Where the fitness value chart emphasises the solutions within the generation, the Mean Fitness Trendline provides insight on whether the overall mean for the fitness objective being analysed is increasing, decreasing or fluctuating around the same value. Through its analysis, one can quickly discern whether the algorithm is successfully exploring the fitness landscape and shifting the population towards local or global peaks or if its struggling to find peaks within the landscape. Moreover, when coupled with the fitness value chart, anomalies in the mean trendline chart (for example if one generation in the population exhibits an abnormally low or high mean fitness value) can be cross referenced to gain a clearer understanding of why an anomaly has occurred and whether it is beneficial or detrimental to the population (figure 3.3).

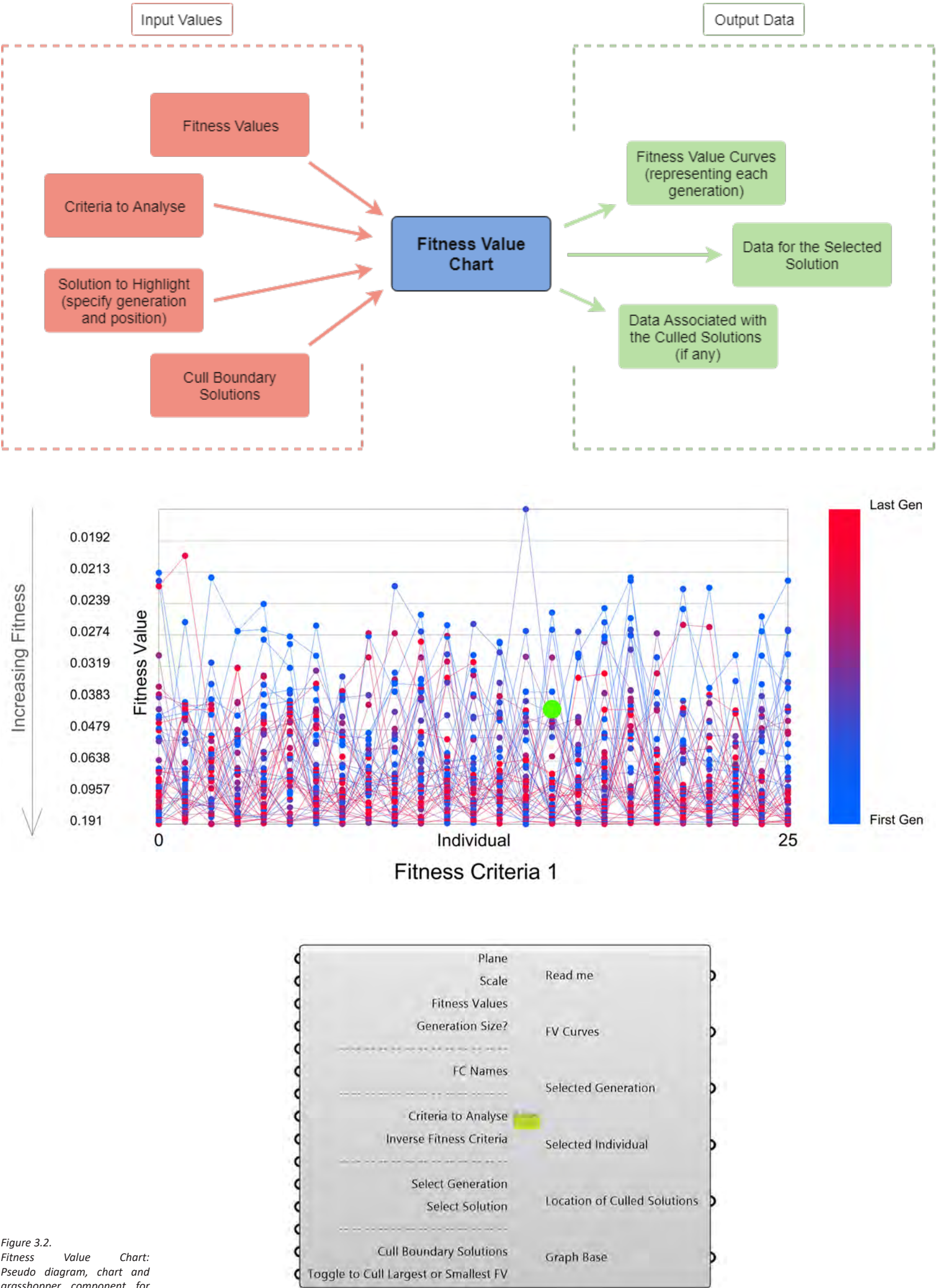


Figure 3.2.
Fitness Value Chart:
Pseudo diagram, chart and
grasshopper component for
the 'fitness value chart'.

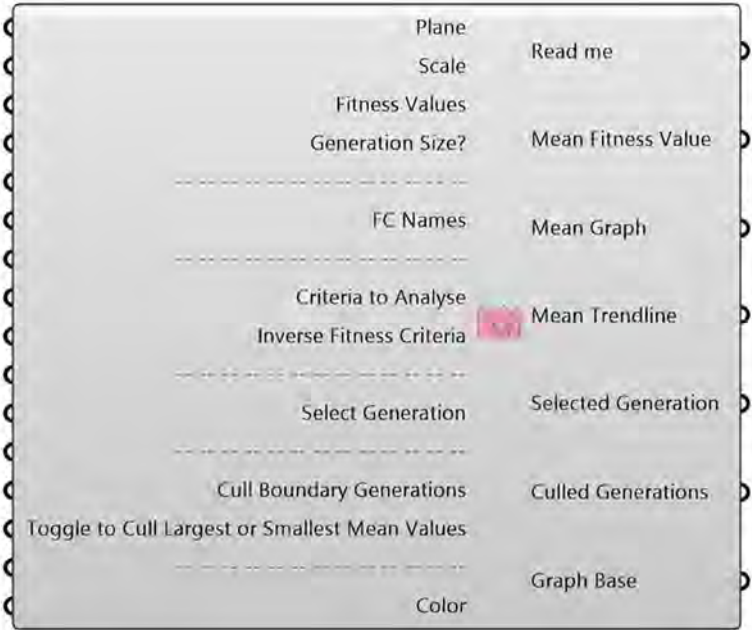
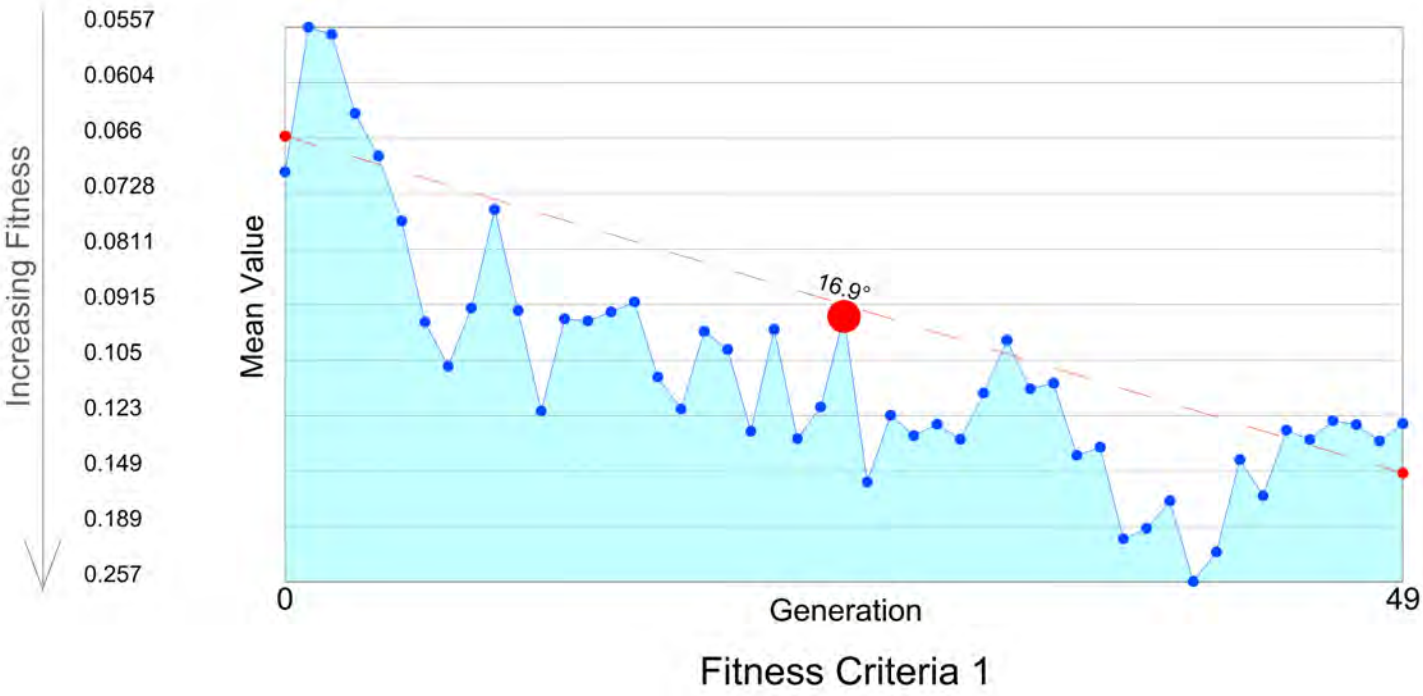
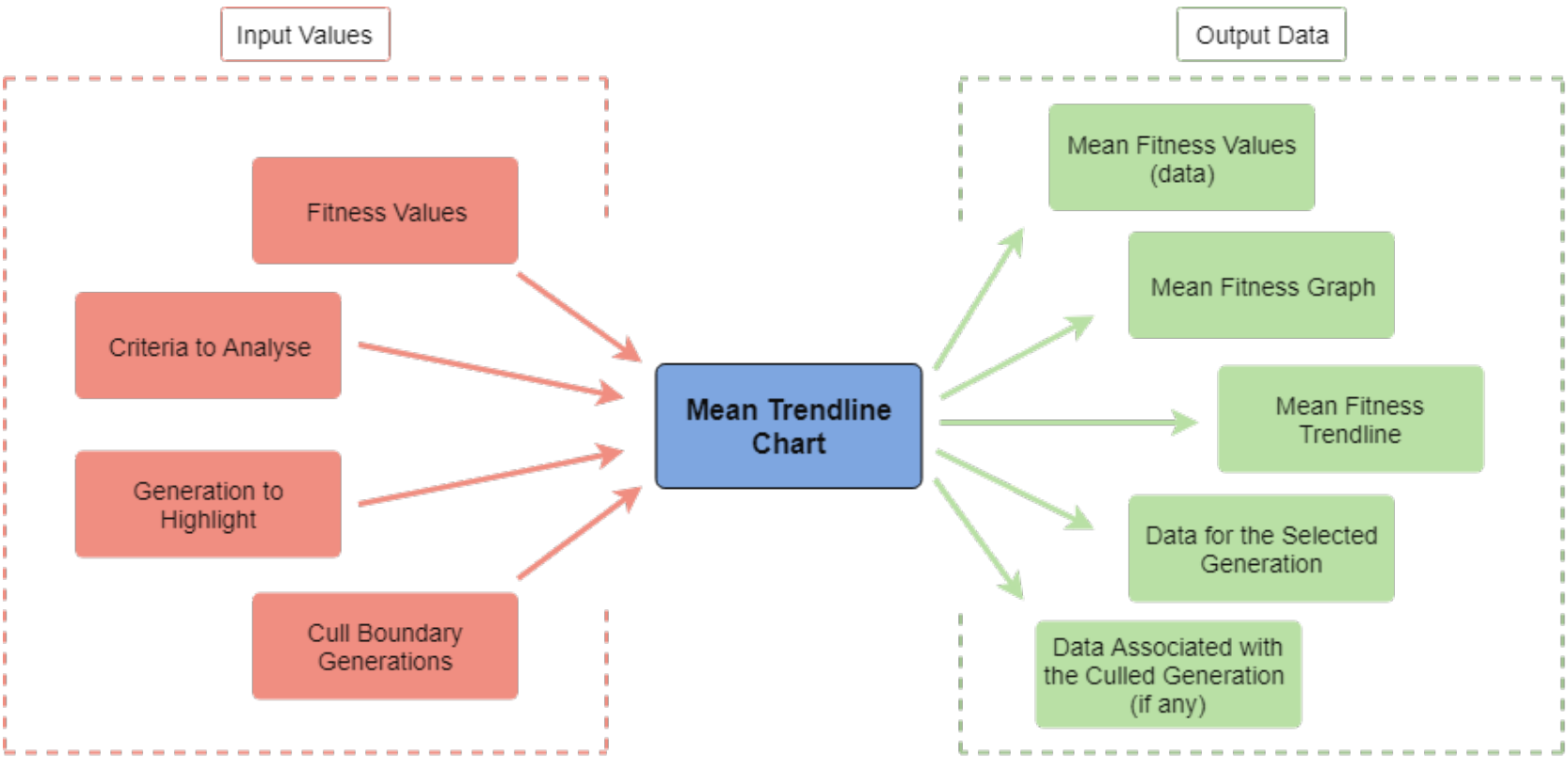


Figure 3.3.
Mean Fitness Trendline Chart:
Pseudo diagram, chart and
grasshopper component for
the 'mean fitness trendline
chart'.

3.5.4. The Standard Deviation

In its purest form, the standard deviation represents the distribution of a set of values from the mean. A low standard deviation factor indicates that most values are clustered around the mean (less variation within the population), while a high standard deviation factor indicates that the values are spread out farther from the mean (more variation within the population). The analysis of the standard deviation of a population from the mean is directly associated (and dependent) on the variance within the population. Through analysing the numerical data associated with each solution in the population, it is relatively straight forward to calculate the variance within each generation. It is important to clarify that the reason variance is calculated per generation rather than for the entire population, is that by doing so, the user achieves a profound understanding as to whether the evolutionary simulation is converging or diverging as it progresses. More importantly, through the variance (and consequently the standard deviation), one can highlight points in the simulation's timeline in which the population experiences sudden convergence or divergence, thus raising a 'red flag' that requires detailed analysis from the user. Moreover, by analysing the variance, it is possible to identify if the population has converged towards a local peak early on in the simulation, which would allow the user to reformulate the design problem to deter the algorithm from over exploiting local optimas.

To plot the standard deviation graphically, three equations must first be solved. The first is the variance value within the generation.

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^n (x_i - \mu)^2$$

Where x is the solution's fitness value and μ is the generation's mean fitness value. Following on from this, the standard deviation is a simple square root of the variance value. As such, the standard deviation of the generation is expressed through the following:

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^n (x_i - \mu)^2}$$

Finally, the standard deviation of the generation is plotted through defining the normal distribution curve, in which the graph is plotted to 3 standard deviations on either side of the mean (this follows the well-established 68-95-99.7 rule in statistics). The normal distribution is calculated through the following formula:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\left(\frac{(x-\mu)^2}{2\sigma^2}\right)}$$

Where σ is the standard deviation factor, μ is the mean fitness value and x is the standard deviation step size.

The robustness of this analytic mode is that it has been completely automated to handle any set of values, regardless of size, in which the associated normal distribution curves for each generation can be visualised and cross referenced to all other generations within the population (although this is the case for all the analytic tools developed, it is more significant for the calculation of the standard deviation due to the need to calculate the above functions for each solution in the population). From all the tools developed, this is in the author's opinion the most beneficial one to the analysis of the evolutionary solver, as it provides visually accessible detailed insight on whether the evolutionary simulation is too explorative or too exploitative, thus allowing the user to revise the design problem and direct the algorithm towards a more efficient navigation of the fitness landscape. Moreover, the Standard Deviation Chart also presents a comparative analysis between the mean fitness value and the variation between the generations. Similar to the Fitness Value Chart, the generations in the Standard Deviation Chart are colour coded from blue to red (oldest to latest), providing the user with clearer insight on the simulation's development (figure 3.4.).

3.5.5. Standard Deviation Trendline

In relation to the Standard Deviation Chart, and in a similar manner to the Mean Value Trendline, the following analytic mode emphasises the comparative analysis between the standard deviation factor between the generations, in which the chart highlights whether the variance throughout the population has increased, decreased or remained stable. Similar to the Mean Value Trendline, the Standard Deviation Trendline plots the standard deviation factor for each generation as a 2-dimensional point, in which the X-axis value is the generation number and the Y-axis value is the standard deviation value for the analysed generation. Moreover, the user is provided with the trendline of how the standard deviation factor has changed throughout the simulation. In design problems with a larger generation count, the cross reference between the Standard Deviation Chart and the Standard Deviation Trendline is pivotal in gaining a comprehensive understanding of how the algorithm is navigating the fitness landscape (figure 3.5.).

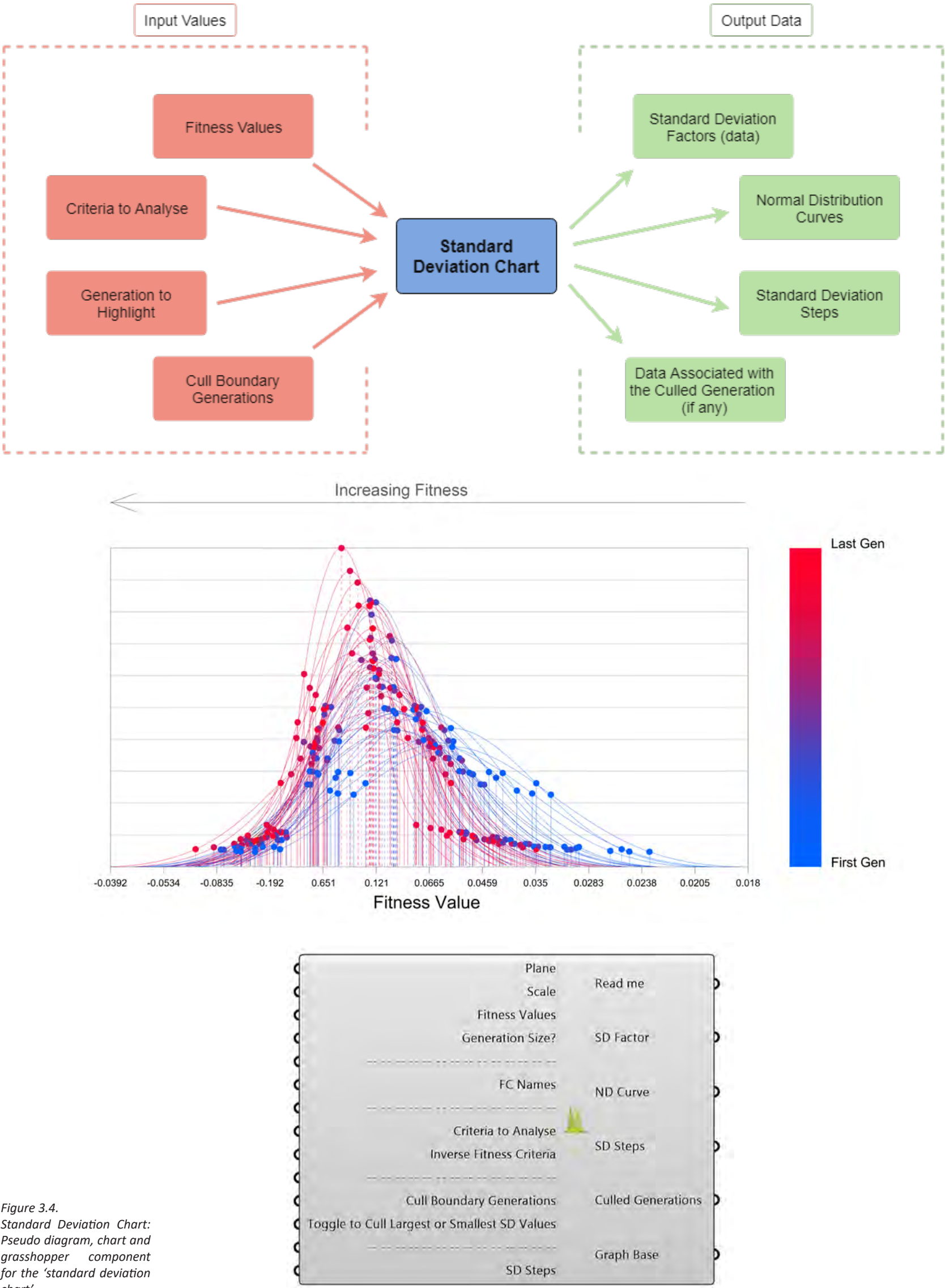


Figure 3.4.
Standard Deviation Chart:
Pseudo diagram, chart and
grasshopper component
for the 'standard deviation
chart'.

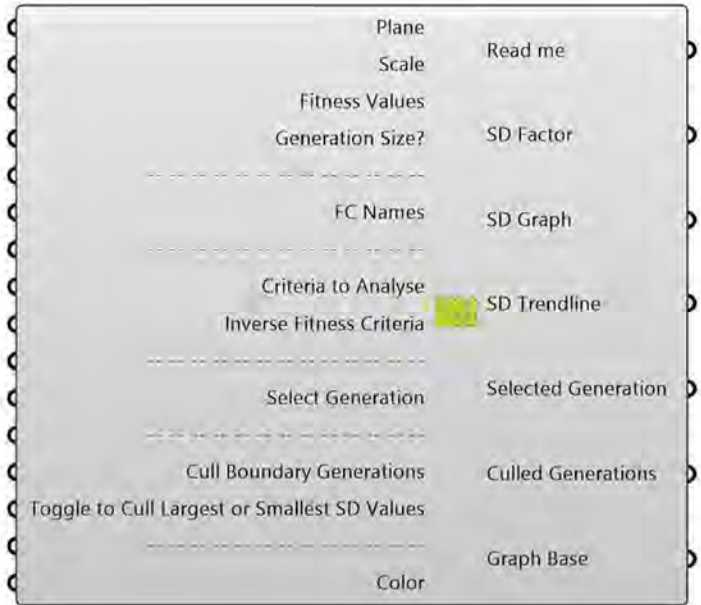
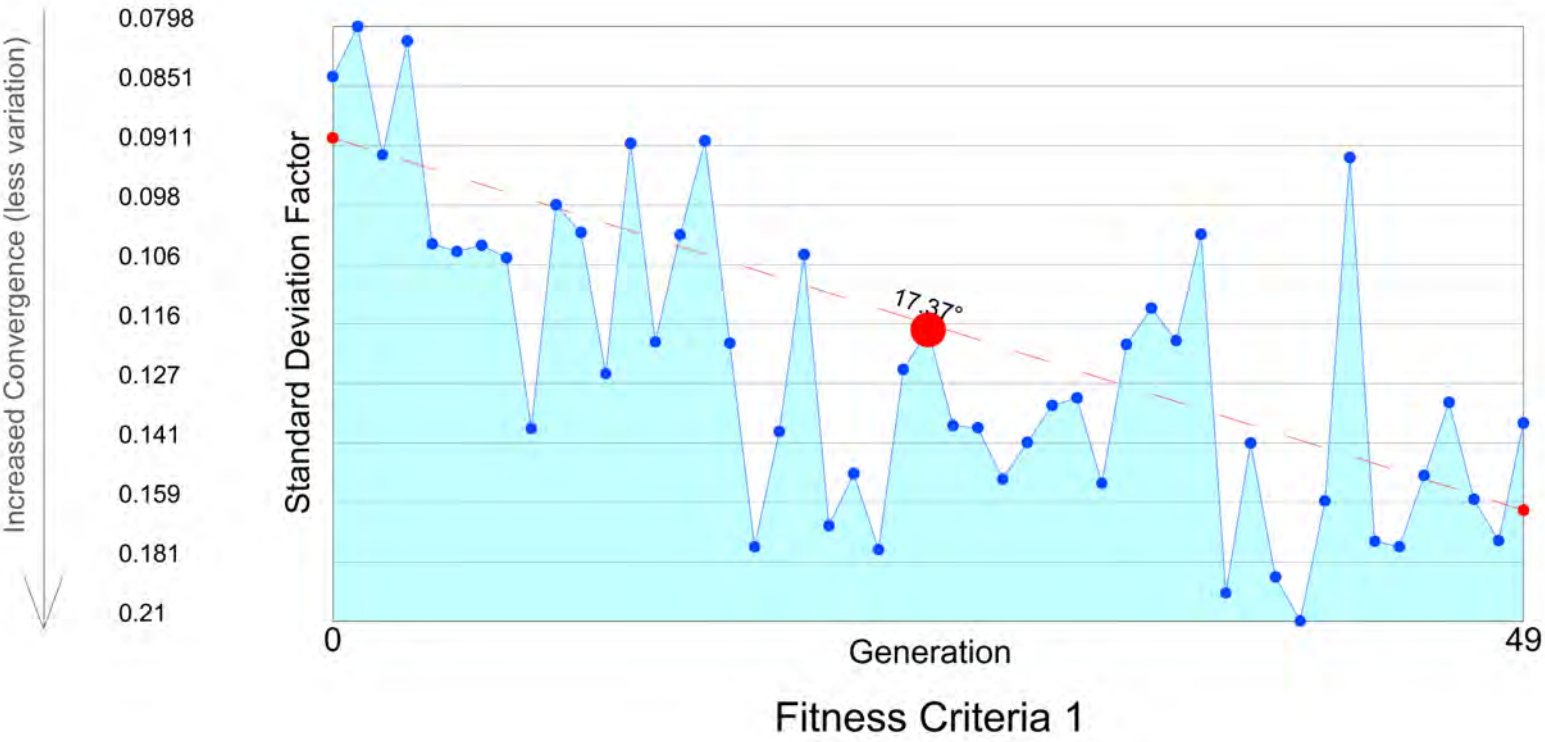
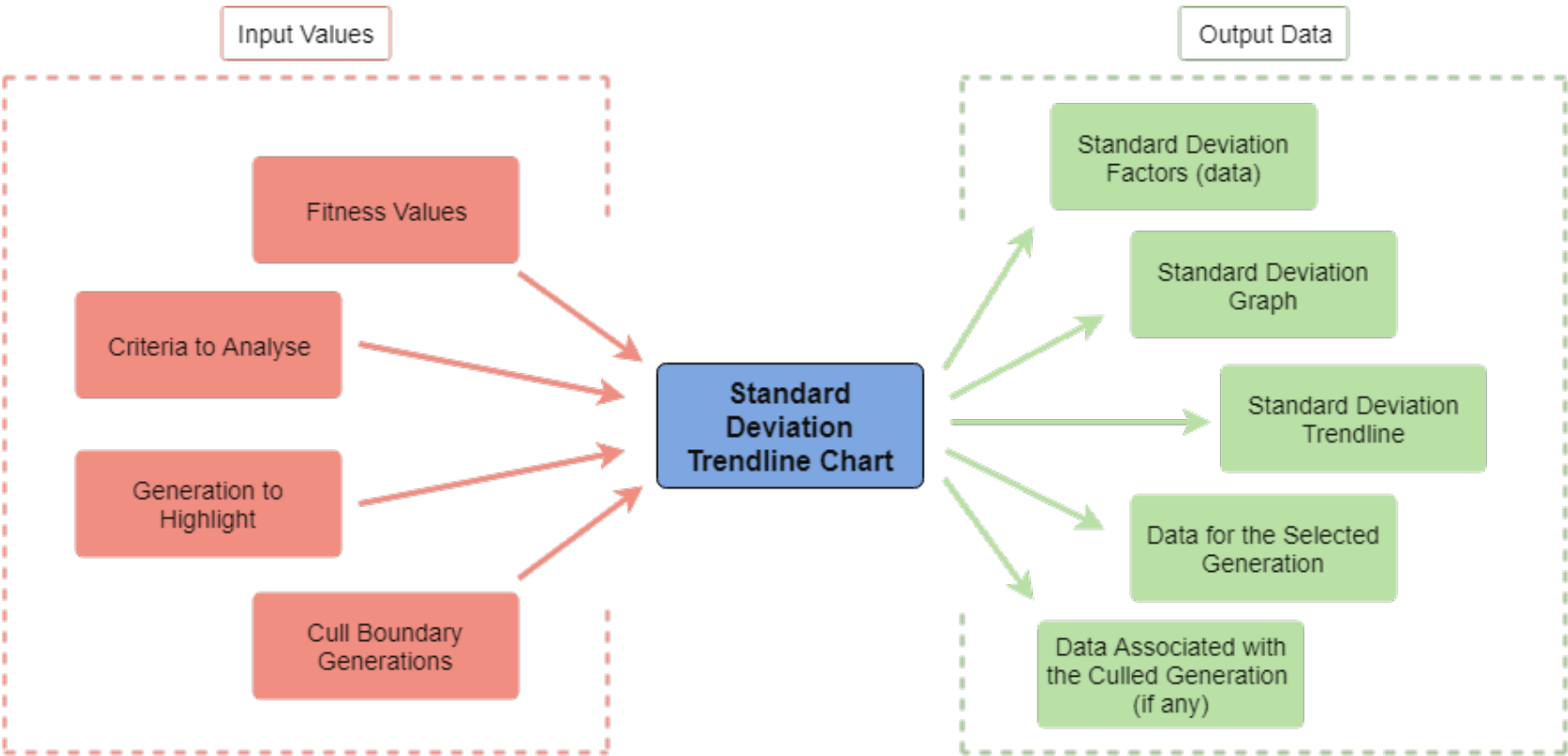


Figure 3.5. Standard Deviation Trendline Chart: Pseudo diagram, chart and grasshopper component for the 'standard deviation trendline chart'.

3.5.6. Objective Space

The challenge of multi objective optimisation lies in the evaluation of solutions in order to determine which one will be selected to move onto the consequent generation, and which one will be deemed to be unfit for selection. In single objective optimisation, this is a relatively straight forward calculation; the fitness value of each solution determines the solution's rank within the population and thus defines which solutions are selected to continue in the simulation. However, as discussed previously, in multi objective optimisation, each solution is associated with multiple fitness values (corresponding to how many objectives are being optimised in the simulation), and although a solution may perform very well for one objective, its performance for a conflicting objective would be relatively lower. To address this issue, dominance is introduced, in which a secondary ranking method (derived from the performance of each solution in each objective) is employed by the evolutionary algorithm to select the solutions that will move forward in the simulation. The concept of dominance was introduced by David Goldberg (1989) in his book titled *Genetic algorithms in search, optimization, and machine learning*. Ever since, it has been integral in the development of multi objective evolutionary algorithms, playing a primary role in most leading multi-objective algorithms to date.

The following example explains how dominance is calculated between 2 solutions in a 2-objective problem, the example assumes that there are two solutions in the objective space, Solution (A) and Solution (B), and that each solution is associated with two fitness values (one value for each objective function), Fitness Value (1) and Fitness Value (2).

If solution (A) outperforms solution (B) in fitness objectives (1) and (2), then solution (A) dominates solution (B). If in contrast, solution (B) outperforms solution (A) in fitness objectives (1) and (2), then solution (B) dominates solution (A). If solution (A) outperforms solution (B) in fitness objective (1), while solution (B) outperforms solution (A) in fitness objective (2), then neither of the 2 solutions dominate one another.

Through ranking each solution in the population with a dominance value, the algorithm selects the solutions that are not dominated by any other solution in the generation as the fittest individuals that will move forward to the next generation. These non-dominated solutions comprise the pareto front, and so in most cases, the pareto front is assumed to contain the fittest solutions in any given generation (Deb, 2008). Figure 3.6. is an example for the calculation of the dominance rank for a 3-objective problem for a single generation comprised from 5 solutions

There is a substantial benefit from visualising the distribution of solutions in relation to one another (the scatter plot approach was put forward by Meisel (1973) and later by Cleveland (1994) for plotting solutions with two or three objectives) with respect to their dominance rank, and their distribution within the pareto front. This provides the user with a clear and informative tool that highlights whether dominance ranking is unintentionally favouring one (or some) objectives over the others and in consequence directing the simulation towards optimising unequally between the objectives. Although the evolutionary solver Octopus provides the user with a visual representation of the objective space and the pareto front, this is provided for each generation independently rather than throughout the entire population (where the objective

space is remapped to the numeric domain of the solutions in the latest generation). As such, the tool developed allows for the comparative analysis of all solutions within the population through a visual representation of their location in the objective space. Moreover, it allows the user to select any generation in the population in order to visualise the pareto front of that generation, as well as highlight the solution location of each individual positioned in the pareto front.

The challenge of calculating the objective space rests on the calculation of the dominance rank for design problems comprising from 3 or more objectives, as this requires the cross reference between a large data-set, a task that could not be performed manually. More importantly, the calculation must be scalable, in which dominance and pareto optimality can be calculated regardless of the generation size, generation count or objective count. However, once achieved, the Objective Space Chart is a robust tool in analysing and understanding the development of the evolutionary simulation that provides the user with a high degree of flexibility, in which one can select which fitness objectives are evaluated; which generation is selected to calculate and visualise its pareto front; and if necessary, to cull solutions from the objective space that are negatively affecting the numeric domain of the objective space (figure 3.7.).

Solution number	Objective 1	
	Objective 1	Objective 2
(a)	7	3
(b)	9	5
(c)	5	2
(d)	6	7
(e)	1	5

For each objective separately, Calculate whether the fitness value of solution (x) is better or worst than the fitness value of solution (x') (if the fitness value of (x) is lower than (x'), it is considered better)									
Solution (a)									
Objective 1					Objective 2				
analysis		Result	Value (worst = 0, better = 1)		analysis		Result	Value (worst = 0, better = 1)	
(a) ? (b)	7 < 9	better	1		(a) ? (b)	3 < 5	better	1	(a) ? (b)
(a) ? (c)	7 > 5	worst	0		(a) ? (c)	3 > 2	worst	0	(a) ? (c)
(a) ? (d)	7 > 6	worst	0		(a) ? (d)	3 < 7	better	1	(a) ? (d)
(a) ? (e)	7 > 1	worst	0		(a) ? (e)	3 < 5	better	1	(a) ? (e)

For each objective separately, Calculate whether the fitness value of solution (x) is better or worst than the fitness value of solution (x') (if the fitness value of (x) is lower than (x'), it is considered better)									
				Solution (b)					
Objective 1				Objective 2					
analysis		Result	Value (worst = 0, better = 1)	analysis		Result	Value (worst = 0, better = 1)		
(b) ? (a)	9 > 7	worst	0	(b) ? (a)	5 > 3	worst	0	(b) ? (a)	5 > 3
(b) ? (c)	9 > 5	worst	0	(b) ? (c)	5 > 2	worst	0	(b) ? (c)	5 > 2
(b) ? (d)	9 > 6	worst	0	(b) ? (d)	5 < 7	better	1	(b) ? (d)	5 < 7
(b) ? (e)	9 > 1	worst	0	(b) ? (e)	5 = 5	worst	0	(b) ? (e)	5 = 5

For each objective separately, Calculate whether the fitness value of solution (x) is better or worst than the fitness value of solution (x') (if the fitness value of (x) is lower than (x'), it is considered <u>better</u>)									
Solution (c)									
Objective 1					Objective 2				
analysis		Result	Value (worst = 0, better = 1)		analysis		Result	Value (worst = 0, better = 1)	
(c) ? (a)	5 < 7	better	1		(c) ? (a)	2 < 3	better	1	(c) ? (a)
(c) ? (b)	5 < 9	better	1		(c) ? (b)	2 < 5	worst	1	(c) ? (b)
(c) ? (d)	5 < 6	better	1		(c) ? (d)	2 < 7	better	1	(c) ? (d)
(c) ? (e)	5 > 1	worst	0		(c) ? (e)	2 < 5	better	1	(c) ? (e)

For each objective separately, Calculate whether the fitness value of solution (x) is better or worst than the fitness value of solution (x') (if the fitness value of (x) is lower than (x'), it is considered <u>better</u>)									
Solution (d)									
Objective 1					Objective 2				
analysis		Result	Value (worst = 0, better = 1)		analysis		Result	Value (worst = 0, better = 1)	
(d) ? (a)	6 < 7	better	1		(d) ? (a)	7 > 3	worst	0	
(d) ? (b)	6 < 9	better	1		(d) ? (b)	7 > 5	worst	0	
(d) ? (c)	6 > 5	worst	0		(d) ? (c)	7 > 2	worst	0	
(d) ? (e)	6 > 1	worst	0		(d) ? (e)	7 > 5	worst	0	

For each objective seperatley, Calculate whether the fitness value of solution (x) is better or worst than the fitness value of solution (x') (if the fitness value of x is lower then it is considered <u>better</u>)									
Solution (e)									
Objective 1				Objective 2					
analysis		Result	Value (worst = 0, better = 1)	analysis		Result	Value (worst = 0, better = 1)		
(e) ? (a)	1 < 7	better	1	(e) ? (a)	5 > 3	worst	0	(e) ? (a)	1 < 7
(e) ? (b)	1 < 9	better	1	(e) ? (b)	5 = 5	worst	0	(e) ? (b)	1 < 9
(e) ? (c)	1 < 5	better	1	(e) ? (c)	5 > 2	worst	0	(e) ? (c)	1 < 5
(e) ? (d)	1 < 6	better	1	(e) ? (d)	5 < 7	better	1	(e) ? (d)	1 < 6

Figure 3.6.
Objective Space (manual calculation): The manual calculation of the dominance value of solutions within the objective space for a simple problem comprised from 3 fitness objective and 5 solutions.

Fitness Values	
Objective 2	Objective 3
3	3
5	3
2	2
7	2
5	4

Values of other solutions (x')			
Objective 3			
analysis		Result	Value (worst = 0, better = 1)
a) ? (b)	3 = 3	worst	0
a) ? (c)	3 > 2	worst	0
a) ? (d)	3 > 2	worst	0
a) ? (e)	3 < 4	better	1

Calculate if solution (x) is dominated			
If (x) is weaker than (x') in all three objectives, then (x) is considered to be dominated by (x')			
Solution (a)			
Dominance Value			
Total (how many solutions does (x) dominate?)	Dominated? (yes=1, no=0)	Dominance Value	In Pareto Front
1 + 1 + 0	2	<u>1</u>	<u>NO</u>
0 + 0 + 0	0		
0 + 1 + 0	1		
0 + 1 + 1	2		

Values of other solutions (x')			
Objective 3			
analysis		Result	Value (worst = 0, better = 1)
b) ? (a)	3 = 3	worst	0
b) ? (c)	3 > 2	worst	0
b) ? (d)	3 > 2	worst	0
b) ? (e)	3 < 4	better	1

Calculate if solution (x) is dominated			
If (x) is weaker than (x') in all three objectives, then (x) is considered to be dominated by (x')			
Solution (b)			
Dominance Value			
Total (how many solutions does (x) dominate?)	Dominated? (yes=1, no=0)	Dominance Value	In Pareto Front
0 + 0 + 0	0	<u>2</u>	<u>NO</u>
0 + 0 + 0	0		
0 + 1 + 0	1		
0 + 0 + 1	1		

Values of other solutions (x')			
Objective 3			
analysis		Result	Value (worst = 0, better = 1)
c) ? (a)	2 < 3	better	1
c) ? (b)	2 < 3	better	1
c) ? (d)	2 = 2	worst	0
c) ? (e)	2 < 4	better	1

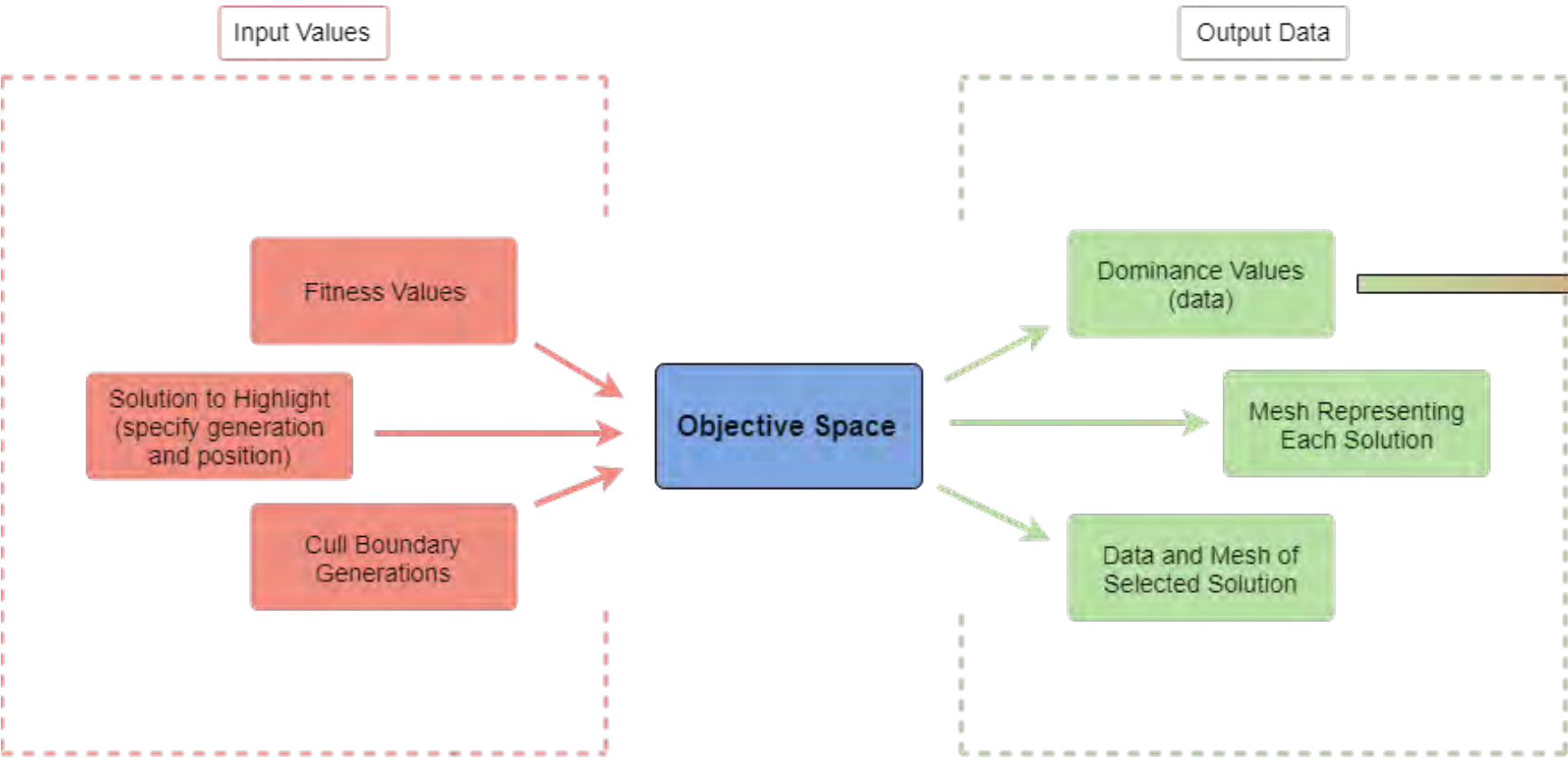
Calculate if solution (x) is dominated			
If (x) is weaker than (x') in all three objectives, then (x) is considered to be dominated by (x')			
Solution (c)			
Dominance Value			
Total (how many solutions does (x) dominate?)	Dominated? (yes=1, no=0)	Dominance Value	In Pareto Front
1 + 1 + 1	3	<u>0</u>	<u>YES</u>
1 + 1 + 1	3		
1 + 1 + 0	2		
0 + 1 + 1	2		

Values of other solutions (x')			
Objective 3			
analysis		Result	Value (worst = 0, better = 1)
d) ? (a)	2 < 3	better	1
d) ? (b)	2 < 3	better	1
d) ? (c)	2 = 2	worst	0
d) ? (e)	2 < 4	better	1

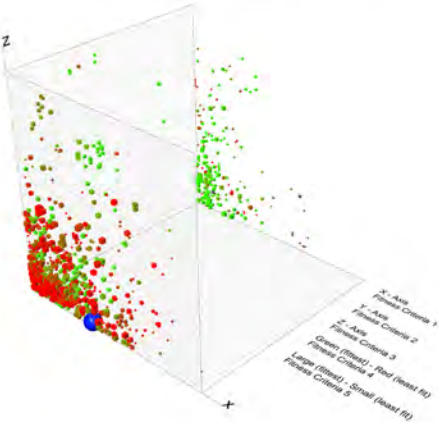
Calculate if solution (x) is dominated			
If (x) is weaker than (x') in all three objectives, then (x) is considered to be dominated by (x')			
Solution (d)			
Dominance Value			
Total (how many solutions does (x) dominate?)	Dominated? (yes=1, no=0)	Dominance Value	In Pareto Front
1 + 0 + 1	2	<u>1</u>	<u>NO</u>
1 + 0 + 1	2		
0 + 0 + 0	0		
0 + 0 + 1	1		

Values of other solutions			
Objective 3			
analysis		Result	Value (worst = 0, better = 1)
e) ? (a)	4 > 3	worst	0
e) ? (b)	4 > 3	worst	0
e) ? (c)	4 > 2	worst	0
e) ? (d)	4 > 2	worst	0

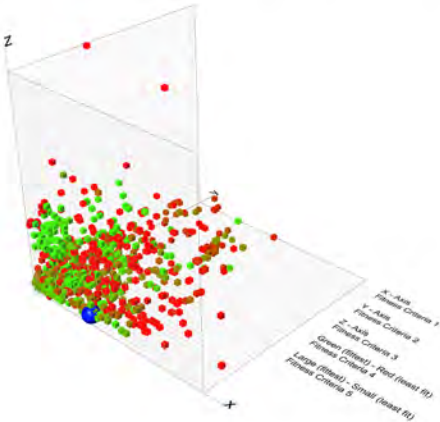
Calculate if solution (x) is dominated			
If (x) is weaker than (x') in all three objectives, then (x) is considered to be dominated by (x')			
Solution (e)			
Dominance Value			
Total (how many solutions does (x) dominate?)	Dominated? (yes=1, no=0)	Dominance Value	In Pareto Front
1 + 0 + 0	1	<u>0</u>	<u>YES</u>
1 + 0 + 0	1		
1 + 0 + 0	1		
1 + 1 + 0	2		



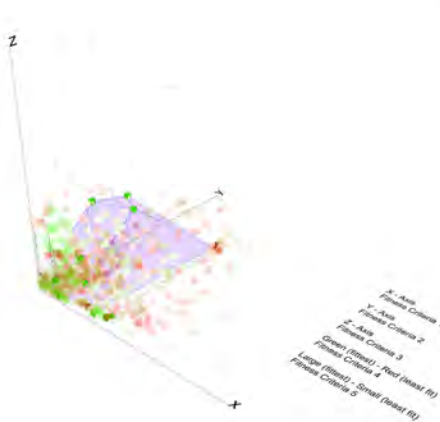
Distribution of solutions within the objective space



Distribution of solutions after the culling of “extremely” unfit solutions



Calculating and visualising the pareto front for a selected generation



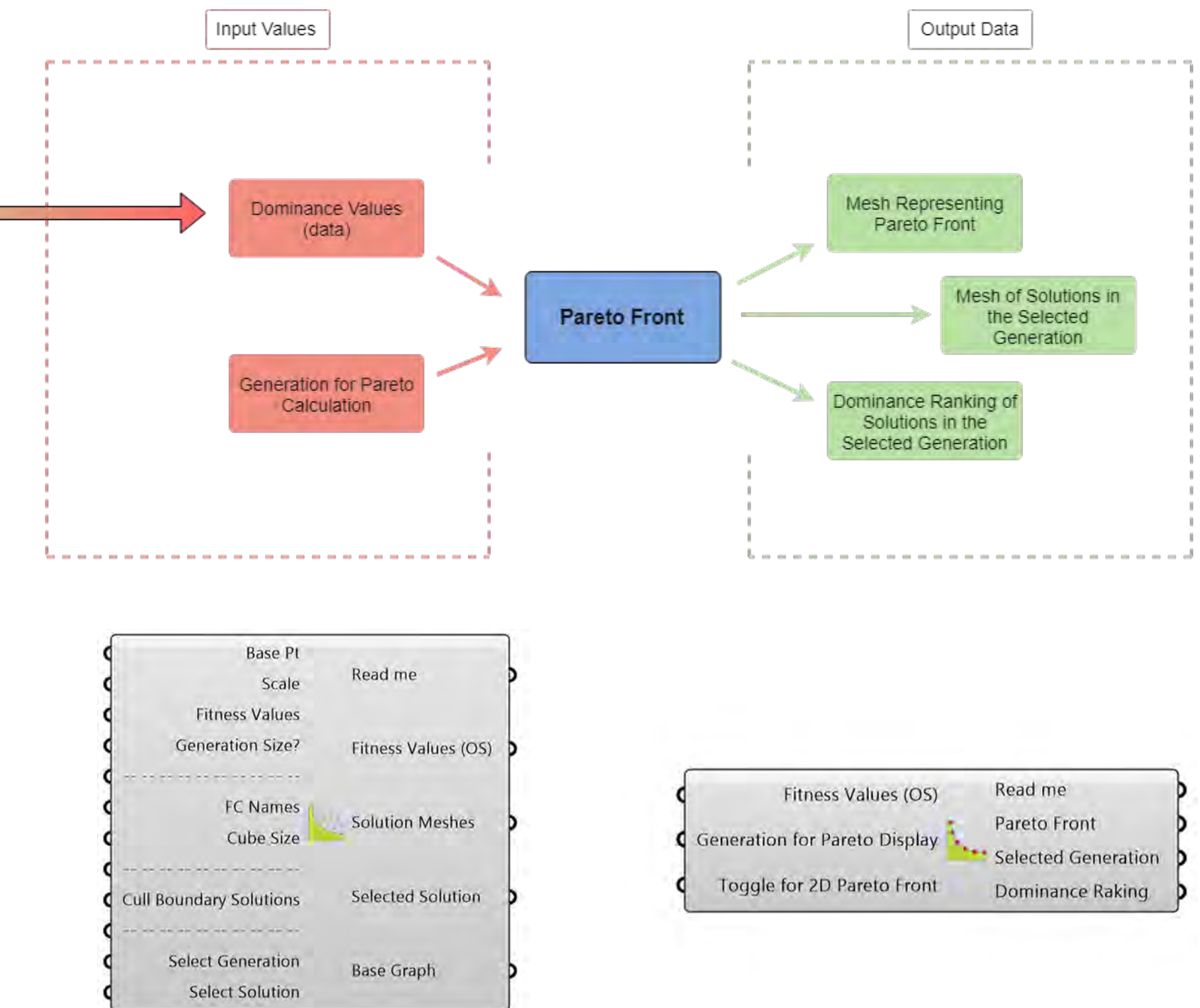


Figure 3.7.
Objective Space and Pareto Front Chart: Pseudo diagram, chart and grasshopper component for the 'objective space chart' and the 'pareto front chart'.

3.5.7. Diamond Fitness Chart

Following on from the Objective Space Chart, the Diamond Fitness Chart (variations of which were suggested in the second half of the 20th century by Manas (1982) called the 'star coordinate system' and later on by Kasanen et al. (1991) called the 'spider web chart' (Miettinen, 2012)) and provides an analytic mode that also compares between the fitness values of the different objectives, but in this case, the analysis is conducted with greater attention given to the solution itself rather than its location within the population. It provides the user with a strong visual aid that differentiates between the different objectives and how they perform in relation to one another. Through this analytic mode, the user is provided with two methods to select a solution for analysis. The first is through a solution's rank; this allows the user to specify the fitness objective and the solution rank in order to analyse the associated solution (for example, fitness objective 3 / fitness rank 0). Through this approach, the user is provided with a detailed account of the solution that corresponds to the selected objective/rank, in which its performance is highlighted for all other objectives, and its location in the population identified. More importantly, the analysis is conducted by comparing the fitness values of all solutions in the population, allowing for a detailed and comprehensive overview of how a particular solution's performance is situated within the population. The second mode of selection is through 'calling' the location of any solution within the population (by specifying the generation and position of the solution) and analysing its fitness rank across the different objectives. In the diamond fitness chart, each axis corresponds to a fitness objective, therefore the chart itself is scalable corresponding to the number of objectives being analysed.

In theory, the fittest solution would be the one that is represented by the smallest diamond with equilateral sides, as this would imply that the solution has been fully and equally optimised to each fitness objective; however, as multi objective problems are usually associated with conflicting objectives, the 'diamond' is usually skewed (i.e. performs well) towards some objectives over the others. Despite this, the significance of the diamond fitness chart rests on its representation of the different fitness values through a single geometric element, in which the user can compare different solutions according to the properties of this geometry (for example, if the user is looking for a solution that is equally ranked for all objectives, he/she is able to analyse the geometric diamond representation of each solution and select the geometries with equilateral sides) (figure 3.8.).

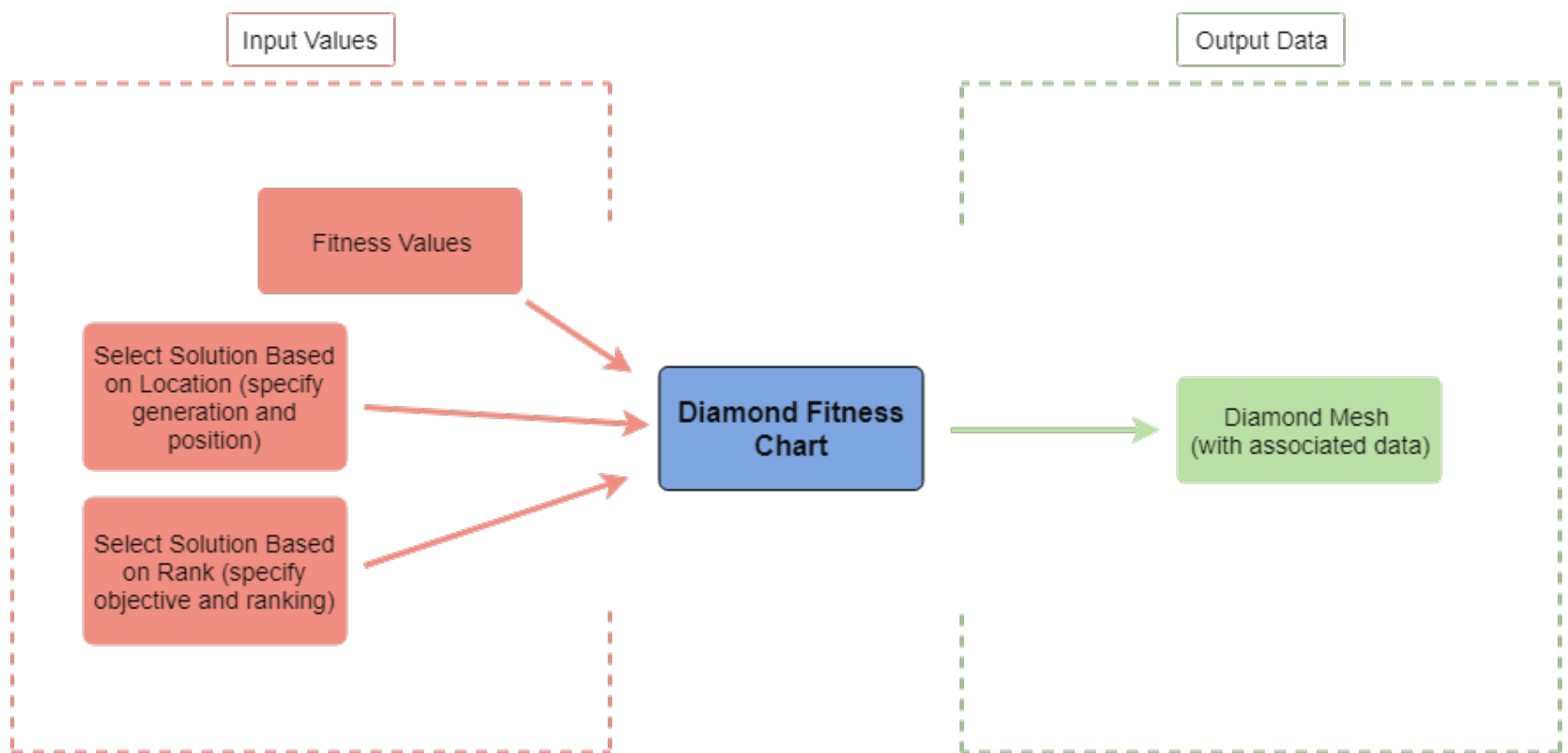
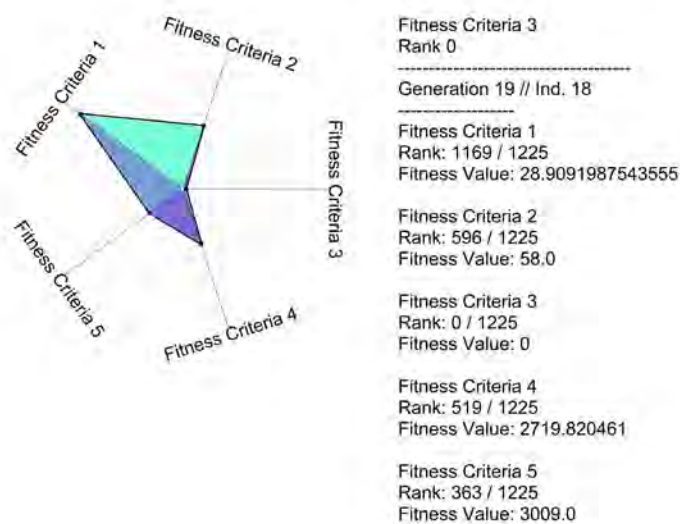
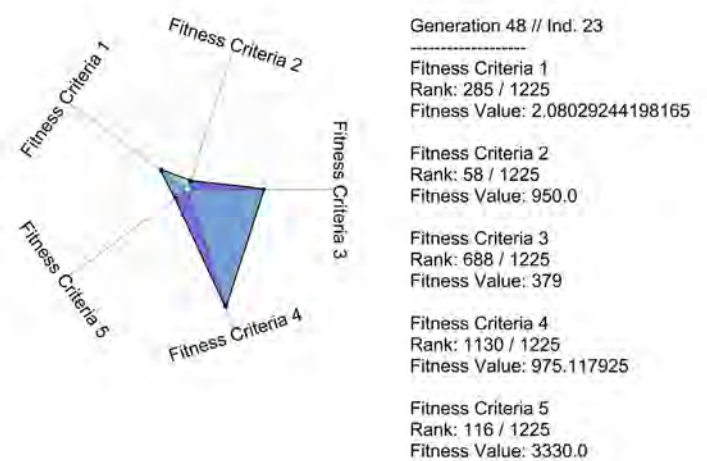
Selecting Solution Based on *Ranking*Selecting Solution Based on *Location*

Figure 3.8.
Diamond Fitness Chart:
Pseudo diagram, chart and
grasshopper component for
the 'diamond fitness chart'.

3.5.8. Parallel Coordinate Plot

The previous two analytic modes evaluated the fitness value of each solution within two distinct domains, the former (objective space) signified the population, while the latter (diamond chart) signified the individual. In this context, the final developed analytic mode aims to combine both domains into one, in which the fitness values of each solution are analysed both individually in addition to within the population. As such, the parallel coordinate plot is utilised as an analytic method that transcribes the fitness value of each solution for each objective respectively (first suggested by Geoffrion et al. (1972)). The chart itself is comprised from multiple Y-axes, each one representing a fitness objective. Therefore, if the simulation was comprised from 3 fitness objectives, the chart is represented through 3 Y-axes, in which each axis represents a different fitness objective. The challenge lies in the fact that each objective may be originally bound within a different numeric domain, therefore, in order to properly conduct a 1:1 analysis of each solution's fitness values, the fitness objectives must all be remapped to lie within the same domain (refer to Li et al. (2017) for more information on how to read data plotted on parallel coordinate plots through a comparison between different evolutionary algorithms).

In each Y-axis, the solution's fitness value is plotted as a 2-dimensional point, and so by connecting the points between the different Y-axes, each solution in the population would be represented through a single polyline. Once all solutions within the population are represented with the parallel coordinate plot, the user can instantaneously identify which objectives are in conflict with one another and confirm whether it complies with the original intentions of the design problem (Inselberg, 1997). This becomes an invaluable 'debugging' tool in very complex design problems, as in such problems, it becomes more difficult to determine which objectives are in conflict with one another. Additionally, the tool is developed to equip the user with the option of choosing which objectives to analyse, this is highly beneficial in instances where the user wants to conduct a thorough analysis on specific objectives in isolation from other data in the simulation. As in the other charts, the polylines representing the solutions are colour coded through a gradient from blue to red in which blue represents the oldest solution while red represents the latest (figure 3.9.).

Through the parallel coordinate plot, a more detailed evaluation is conducted in order to extract additional information from the comparative analysis of the fitness values of each solution within the population. This results in defining multiple selection criteria that assist the user in highlighting specific solutions in the population that exhibit key characteristics. These criteria are explained below:

The first criteria highlights the fitness values that have been repeated the most in the population; more importantly, it also highlights all of the solutions associated with that repeated fitness value. In doing so, the user can conduct further analysis on the characteristics of the highlighted solutions, and whether there exists an emergent trait between them. When analysing the chart according to this method, the user is provided with the polylines that represent each solution and the location of each solution within the population (figure 3.10.).

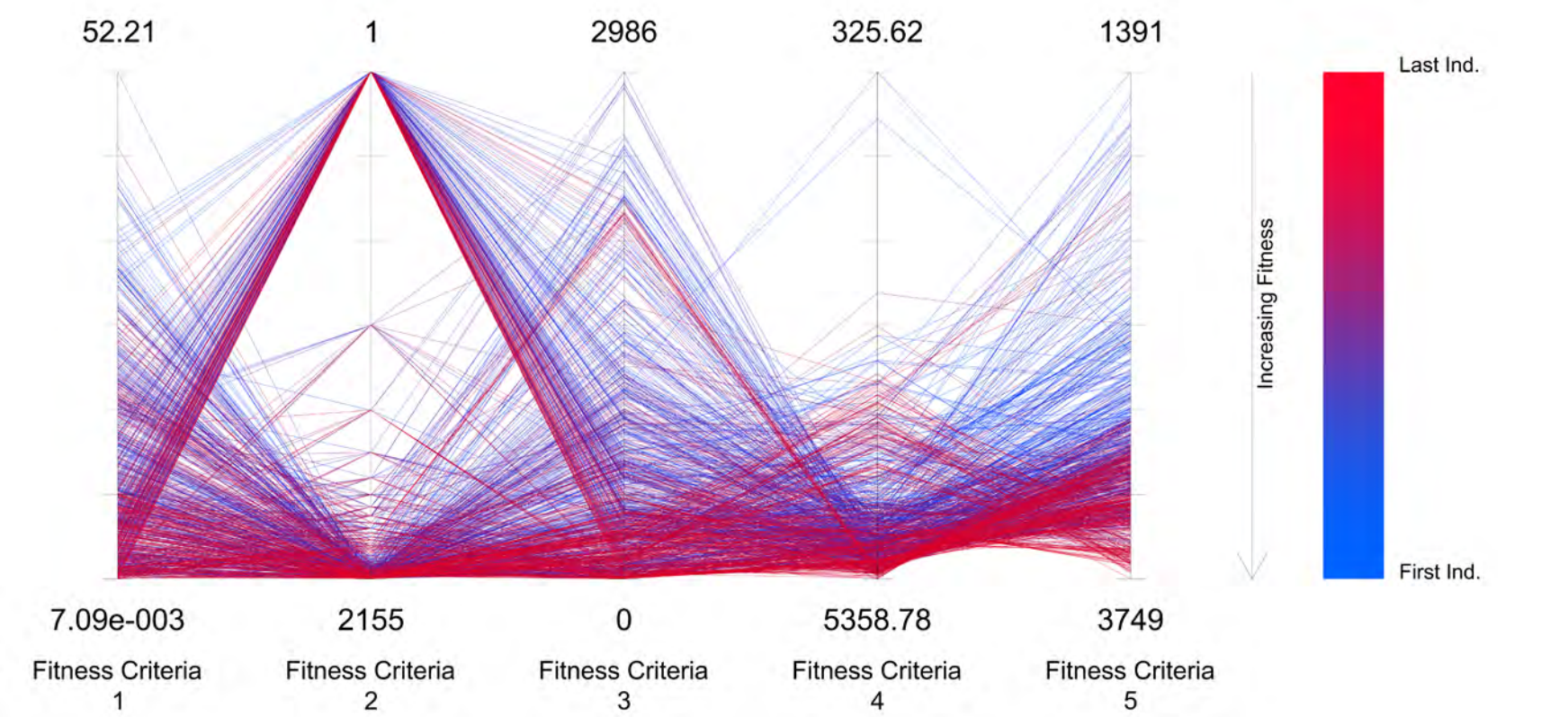
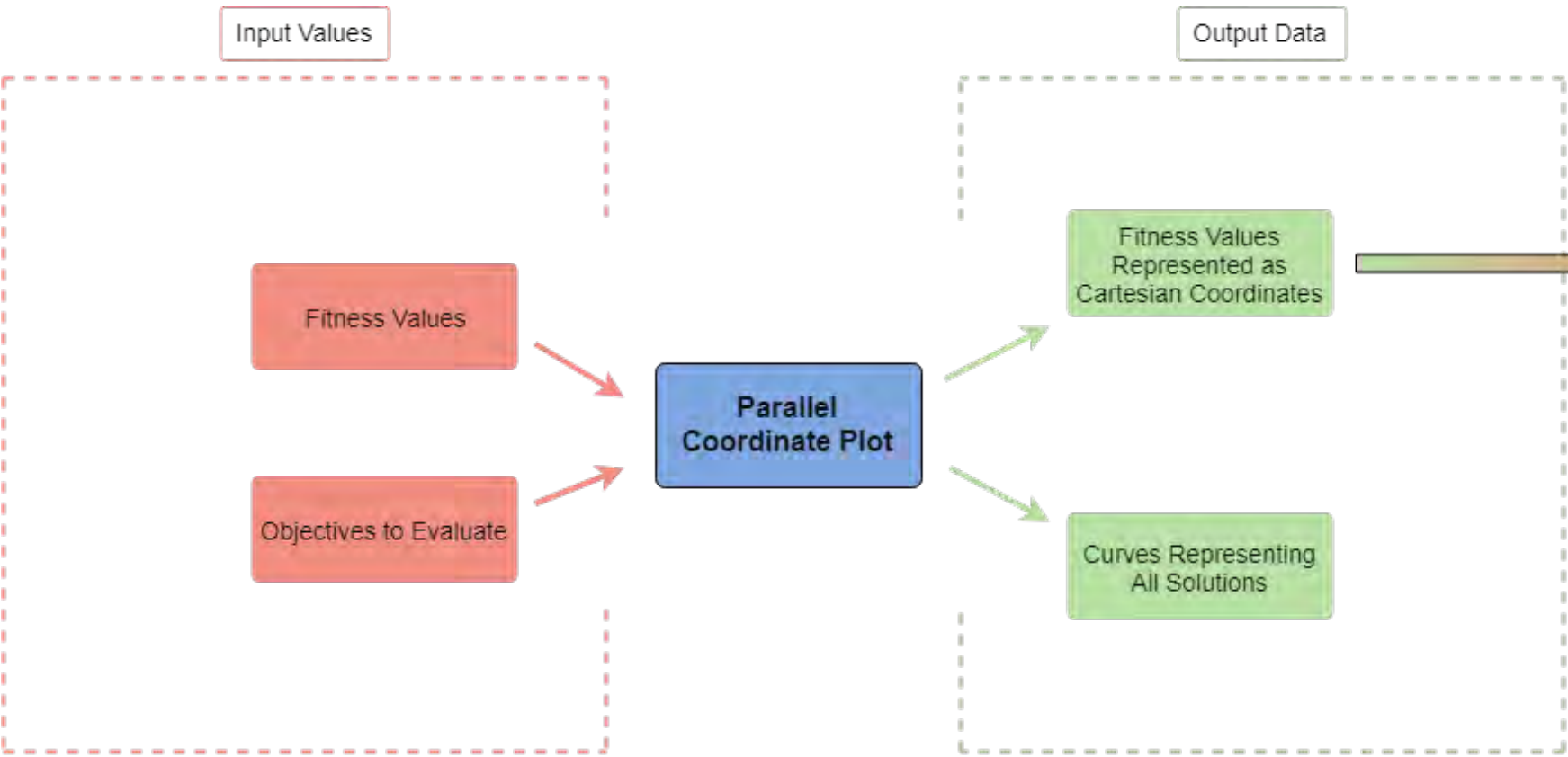
The second method of analysis evaluates the fitness values of each solution based on their ranking amongst other solutions (as opposed to the fitness's absolute value) and sorts the solutions

according to their average rank. This provides the user with the solutions that are highly ranked across the different fitness objectives. It must be pointed out that through this selection method, it has been observed that in some instances the top solutions exhibit similar traits, therefore as a criteria for selecting variation between different solutions, this method does not always serve as an optimal approach (figure 3.11.).

The last selection method analyses the relative difference between the ranking of each solution's fitness value. This is calculated through the following (r_i is the solution's Ranking for the specific fitness criteria):

$$Relative\ Difference = (|r_2 - r_1|) + (|r_3 - r_2|) + (|r_4 - r_3|) \dots + (|r_n - r_{n-1}|)$$

This allows the user to find solutions that are equally ranked for all the objectives without the necessity to compute the average. As this method performs the calculation across the entire population, the user is provided with a full range of 'relative difference' values to choose from (these are sorted from least difference to most difference). As with the previous methods, the polyline representing the selected solution is highlighted in the graph and its location in the population is identified (figure 3.12.).



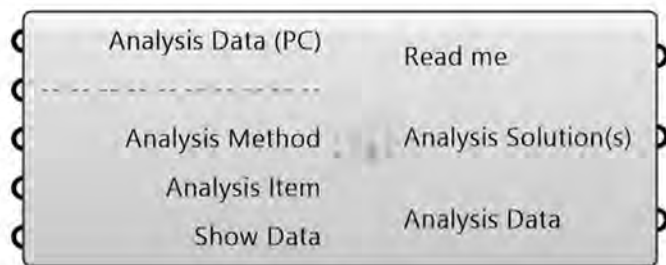
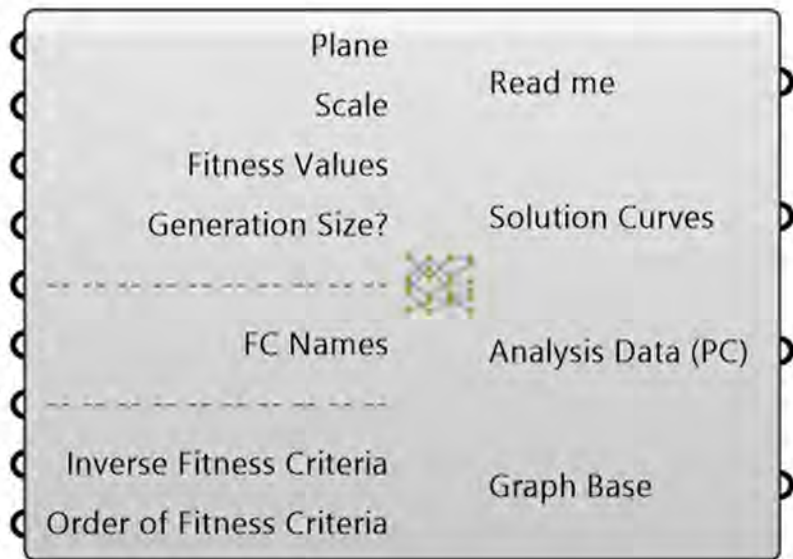
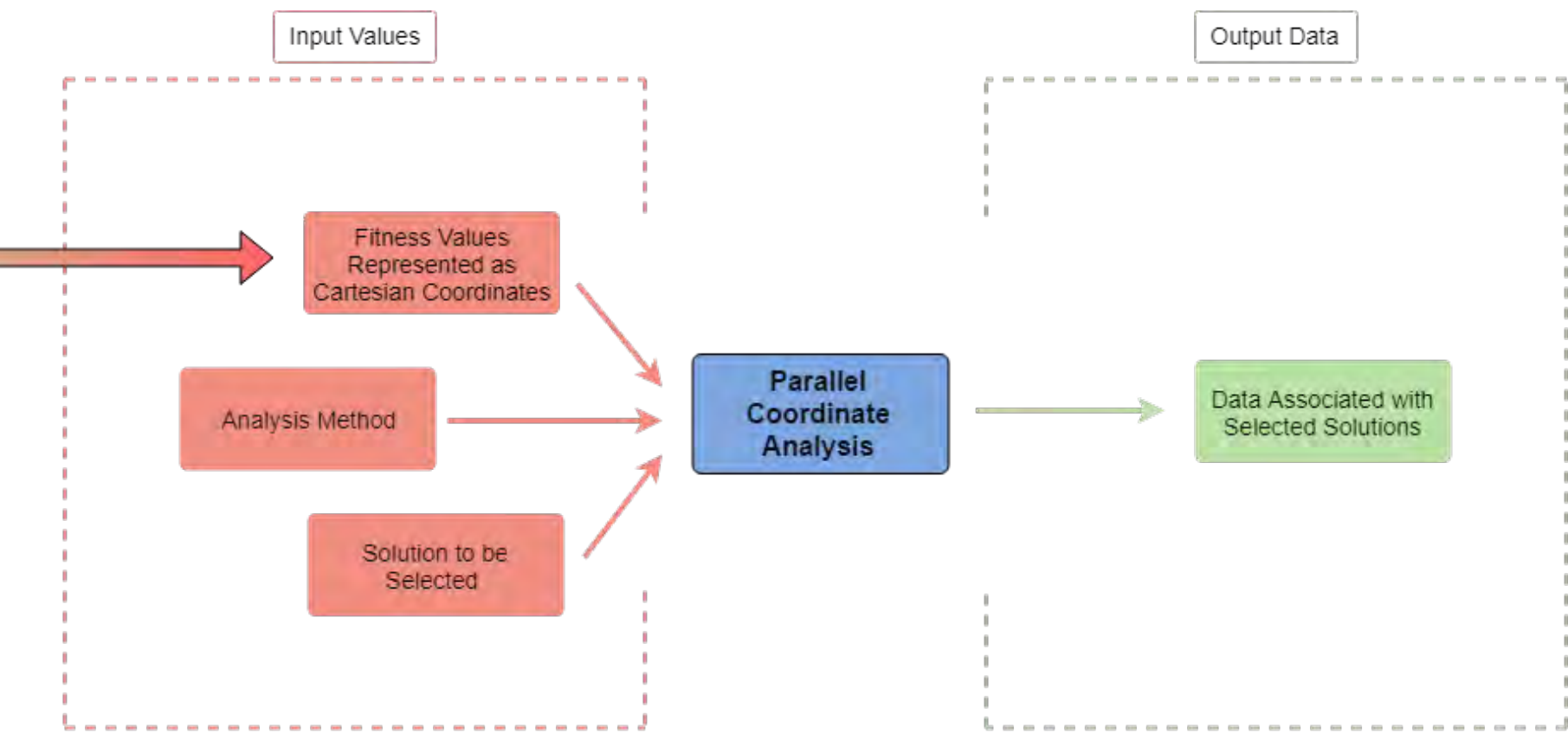


Figure 3.9.
Parallel Coordinate Plot:
Pseudo diagram, chart and
grasshopper component
for the 'parallel coordinate
plot'.

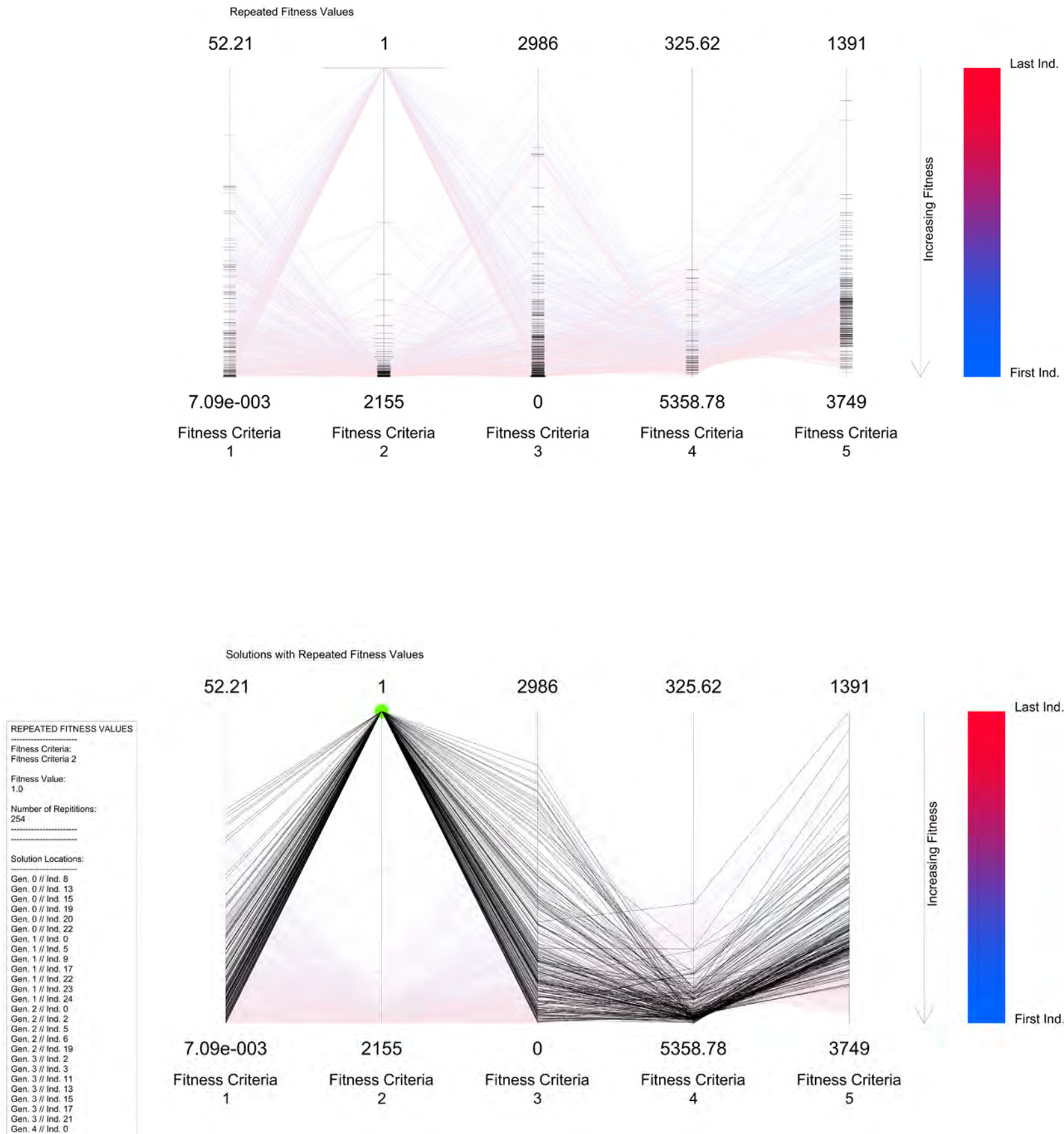


Figure 3.10.
Repeated Fitness Values:
Graphical representation of
the most repeated fitness
values (top) and the solutions
associated with the most
repeated fitness values.

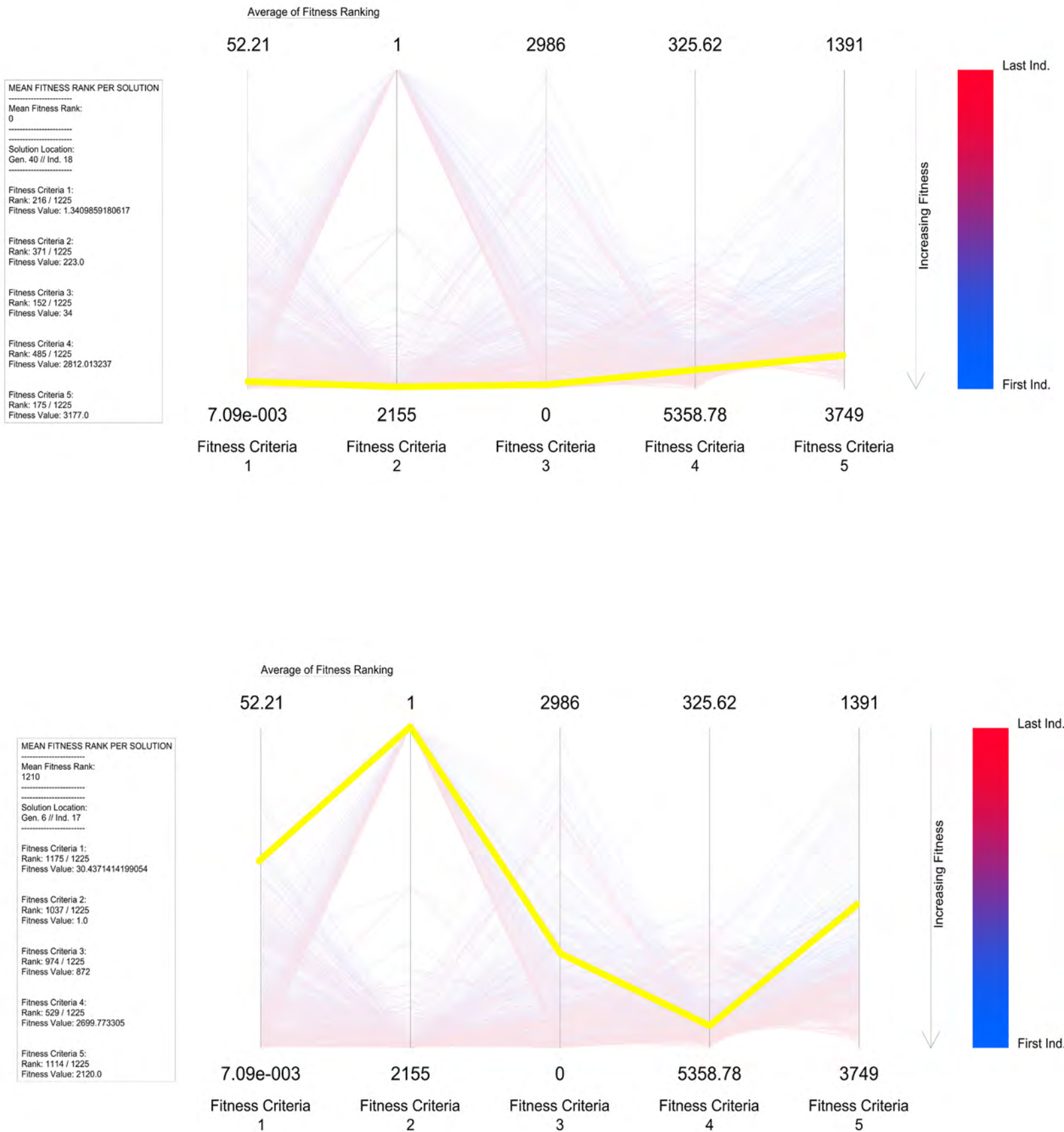


Figure 3.11.
Average Fitness Ranking:
Selecting solution based on
their average fitness ranking.
The top image presents the
fittest solution and the bottom
image presents the least fit
solution.

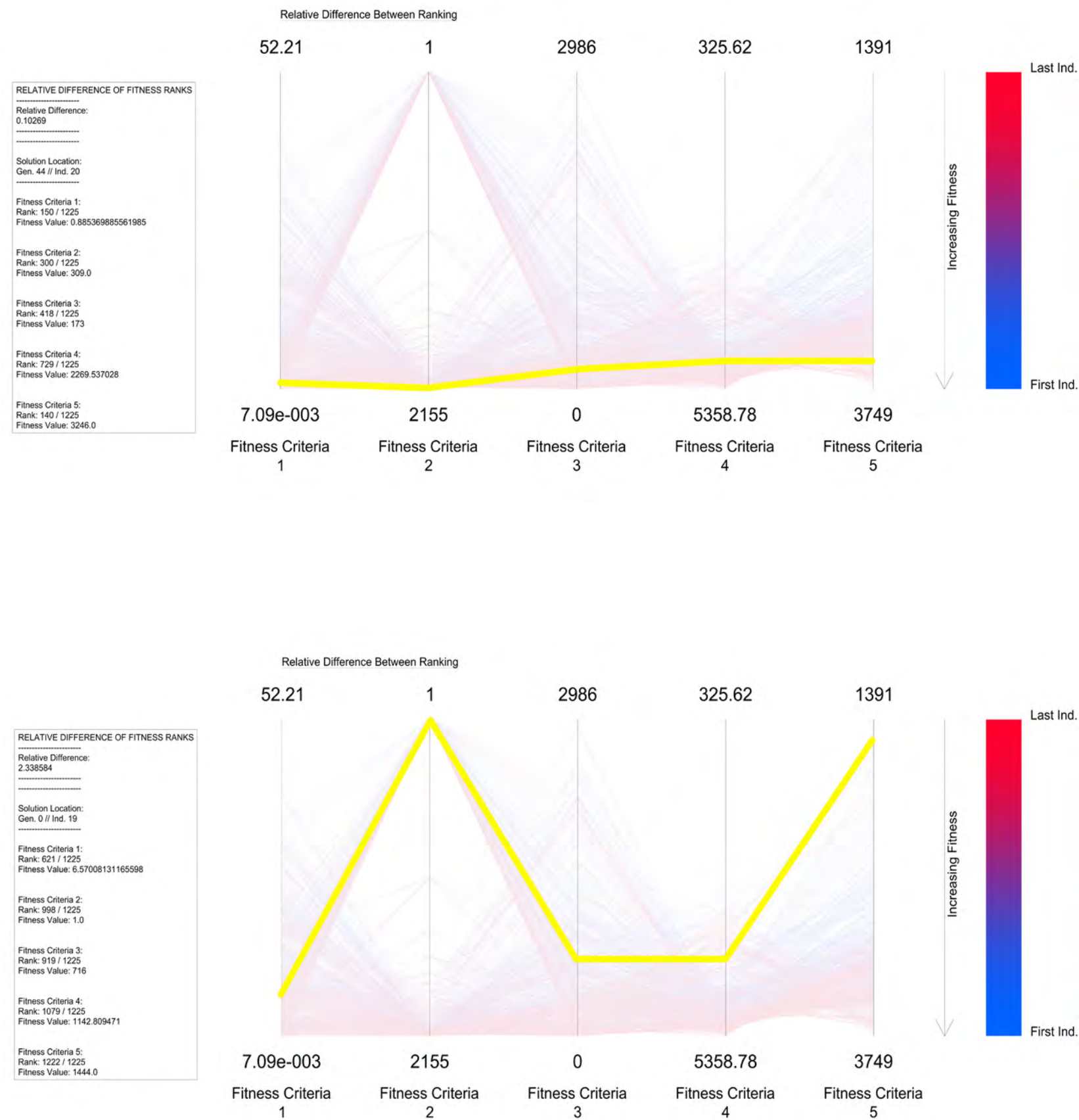


Figure 3.12.
Relative Difference Ranking:
Selecting solutions based
on their relative difference
ranking. The top image
presents the fittest solution
and the bottom image
presents the least fit solution.

3.6. The Genotype and the Phenotype

The algorithmic workflow is vital in ensuring for an efficient application of an evolutionary simulation in design that allows for an equally efficient approach to the extraction and analysis of the complete data set outputted by the algorithm. To achieve this, focus is shifted from the phenotype in favour of the genotype. In current applications of evolutionary simulations in design, the phenotype (the physical representation of the solution) is most coveted; however, in doing so, the computational load increases significantly, due to the necessity to compute, store and output the phenotypes (the geometric meshes) for each solution in the population. This is one of the primary causes for current applications of evolutionary solvers to analyse and extract a sample of the population, as it was through this that a balance was struck between computational load and data generated.

What if the phenotype was no longer necessary as an output? This does not mean the phenotype is no longer important, but instead allows the user to analyse the numerical data associated with every solution in the population without the necessity of also computing the phenotype of every solution in the population (a task that is usually associated with the solver crashing). In this context, the genotype (the genetic code) of each solution is given precedence over the phenotype. Therefore, rather than compute and store each phenotype 'live' within the algorithmic run, the design problem is reformulated so that the genotype of each solution is recorded, stored and outputted by the simulation. The computational impact of achieving this is considerably substantial; It has been recorded by the author that the file size associated for storing the phenotypes for a population comprised from 10,000 solutions is 11.3 Gigabytes; while in contrast, the files size associated with storing the genotypes of the same population is 914 Kilobytes. More importantly, through employing this method, the genotype of any solution in the population can be recalled (through identifying the solution's location) and used to reconstruct the associated phenotype. Storing the genotype over the phenotype has been a vital approach that has allowed full advantage to be taken of the analytical tools explained above, as by doing so, any (or all) phenotypes in the population can be both analysed and reconstructed. An output that was previously unattainable.

3.7. Discussion

The analytic tools and methods developed and explained throughout this chapter form a significant part of the research. Through their utilisation, the focus in the application of evolutionary computation in design shifts from the algorithm to the design problem. Therefore, the impact of the tools developed on the evolutionary process are outlined below:

- Significant control is attained over the levels of variation and/or convergence in the evolutionary simulation. Through the detailed analysis of the numerical results, variation is directed through a decision-making process that is better informed and less arbitrary (as with current applications of the process in design). This is achieved through multiple fronts:
 - An efficient navigation of the fitness landscape through a more precise control over the algorithmic parameters that direct the simulation towards increased or decreased variation and/or convergence.
 - An efficient navigation of the fitness landscape through a reformulation of the design problem. More importantly, reformulating the design problem to allow for a less 'noisy' fitness landscape (one that can be easily navigated) without sacrificing the problem's complexity.
- The occurrence of 'Anomalies' – solutions generated by the algorithm that could not be computed – are identified and their location in the population is highlighted. This allows for the reconstruction of the anomaly through its genotype and thus the reformulation of the design problem to inhibit their occurrence.
- The independent and comparative analysis of the fitness values for each solution's fitness objectives, allowing for emergent behaviour within the simulation to be observed locally (within one objective), regionally (between some objectives) and globally (amongst all objectives). In doing so, the design problem is reformulated and directed towards either increasing or decreasing the occurrence of the observed emergent patterns.
- Through the comparative analysis of all solutions within the population, primarily through the parallel coordinate plot; selection criteria that are external to the evolutionary simulation are utilised to rank the solutions within the population according to each solution's performance to the fitness objectives both independently and collectively.
- Through storing the genotype of each solution instead of the phenotype, the population size generated within the evolutionary process is substantially increased due to the significant decrease in the computational load required to run the simulation.
- The ability to locate any solution (through identifying its position in the population) and highlight its location within all of the analytic tools developed. This allows for the comparative analysis of the fitness values of a specific solution to the rest of the population. More importantly, through reconstructing the solution's phenotype, the design problem can be reformulated to reduce the size of the search space to a domain that is closer to the preferred solution.

Through the above, the tools and methods developed have ensured that the experiments conducted within the research were founded on the set up of well formulated design problems. Moreover, their utilisation as a feedback mechanism is critical towards debugging the evolutionary simulation from any inefficiencies in its application. The tools facilitated the classification and sequencing of solutions within the population in response to predetermined evaluative criteria, thus providing a comprehensive analytic framework of the evolutionary run, and the simulation's output.

The significance of employing the developed tools is further highlighted through their ability to efficiently process 'big data' and extract emergent patterns that are only made visible through the local comparative analysis of all values within the complete data set. Where current applications of evolutionary simulations in design have conducted analyses on a sample of the outputted population, in which a limited number of generations were selected for evaluation, the tools developed present a comprehensive analysis of the simulation through their ability to process the data associated with every solution within the population regardless of its size (the only limitation is imposed through the processing power of the machine that the analysis is being performed on).

Design Experiments Part I

4.1. Introduction

The following two chapters conduct multiple experiments that examine the *design problem* when running an evolutionary simulation. Where current practices of the application of evolutionary computation in design are heavily reliant on the evolutionary algorithm itself, the experiments presented highlight how the *formulation* of the design problem, and the statistical analysis of the numerical results generated by the evolutionary algorithm, increase the efficiency of the simulation evolving a fit and diverse population set.

In this context, the experiments developed examine the formulation (and re-formulation) of the design problem through addressing two key stages within the evolutionary process. First, the incorporation of evolutionary developmental principles of *regulation* within the design problem for generating morphological variation; and second, the utilisation of the analysis conducted on the results of the simulation as a generative component that serves as a feedback mechanism to reformulate the design problem.

Regulation

As stated in chapter 2, the science of evolutionary developmental biology attributes morphological variation within (and between) species to processes of genetic regulation rather than genetic duplication, where phenotypic variation is a result of the regulation between genes and body parts and not necessarily a result of the *size* of the phenotype's genome. This associates the development of morphological traits to a more efficient genetic tool set. In design, this puts forward an alternative method to current applications of evolutionary computation, in which optimised variation within the population is driven through regulatory mechanisms rather than a large genepool and/or a complex expression of the design problem.

Through clustering genes into gene sequences, in which different sequences act on different parts of the phenotype, there develops a clear distinction between genes, body parts and fitness objectives. Key to this is their regulation and its impact on generating a population set that is both diverse and optimised. More importantly, in doing so, morphological variation is achieved at three hierarchical stages; locally within each phenotype, regionally between phenotypes of a single generation, and globally between generations within the population.

Analysis

The tools and methods developed in chapter 3 highlight the significance of the thorough analysis of the numerical data associated with every solution generated by the evolutionary simulation, both individually and comparatively, and the impact of the result of the analysis in serving as a feedback mechanism to re-

formulate the design problem. In doing so, irregularities, emergent patterns, premature convergence, lack of optimisation, an inadequate balance between exploration and exploitation, errors in computing the phenotype (which are referred to as anomalies in the experiments presented) and inconsistencies between the relationship of the fitness criteria (as well as many other observations) are addressed through a revision of the design problem. This is in contrast to current applications of evolutionary computation, in which either very limited (or none at all) statistical analysis is conducted on the results; where the majority of the instances in which the analysis is conducted, it is within the framework of understanding the output for selection, rather than serving as a feedback mechanism to reformulate the design problem in order to generate a more efficient output.

4.2. Experiment 1 – Single and Multi-Objective Optimisation

4.2.1. Ambition

The first experiment analyses the effect of incorporating regulatory mechanisms through two different applications. The first is within the framework of a single objective problem (experiment 1A), while the second is within the framework of a multi-objective problem (experiment 1B). Both experiments are presented through a clear delineation between the relationship of genes, body parts and fitness objectives. Moreover, the formulation of the design problems in both experiments is the same, with the only difference being that in the former, the fitness objectives are combined into one objective, whereas in the latter, the fitness objectives remain independent from one another.

The experiments are conducted to analyse the differences between single objective and multi-objective design problems, both in the formulation of the design problem and in the output of each simulation, and the impact of the design problem's expression on the diversity within the population. As such, both experiments are comprised from a relatively small population size of 1,000 solutions that utilise Barcelona's *Eixample* block as the primitive phenotype onto which the simulation is conducted.

4.2.1.1. Location

In 1859 Ildefons Cerdà proposed '*L'Eixample*', an urban solution for accommodating Barcelona's growing population through extending the city's urban fabric beyond its walls. The distribution of functions within the urban plan would later be the primary cause in transforming Barcelona into one of the highest population density cities of Europe (Ajuntament de Barcelona, 2018). Through his new plan, Cerdà aimed to address issues of population growth, building density, unsanitary conditions, illnesses and high mortality rates that were impacting the city's development during the 19th century (figure 4.1.). Cerdà engaged three primary domains – sanitation, circulation, and social equality (Fernández, 1980):

- Sanitation – Addressed through a predominantly statistical-driven approach (Figuerola, 1849) that was the result of an in-depth field analysis of Barcelona and other prominent cities (Boston, Buenos Aires, New York, etc.), the consideration of block orientation, climatology and sun exposure were considered to be decisive in developing a sanitary urban expansion.
- Circulation– A hierarchical street network aimed to create efficient transportation throughout the city to accommodate both pedestrians and vehicles within the same network while generating greater efficiency in visual connectivity through the implementation of chamfered intersections.
- Social Equality – The design attempted to generate the possibility of an ‘endless’ urban expansion of the city, establishing social equality through urban homogeneity.

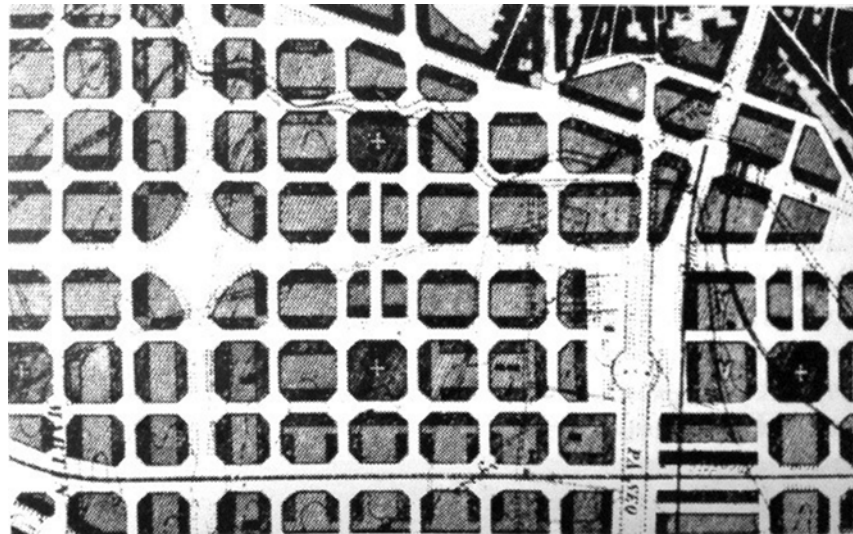
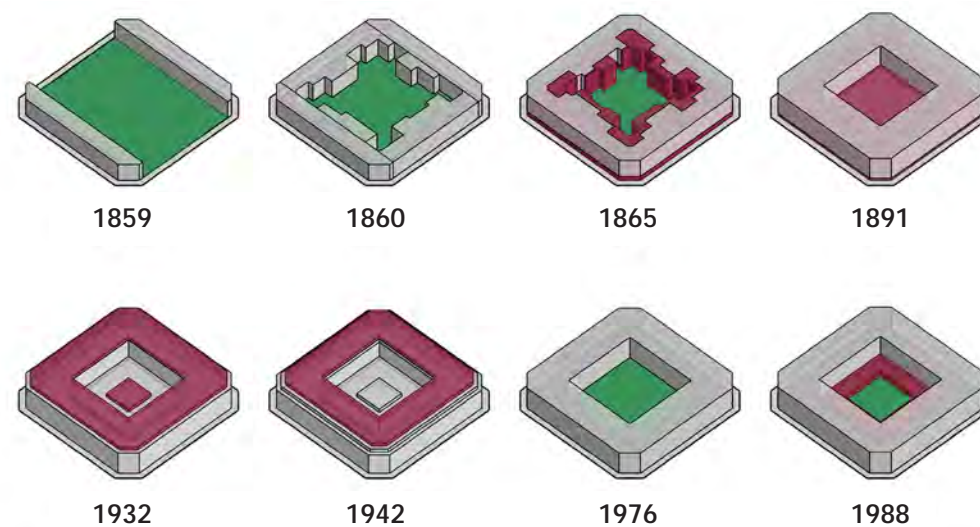


Figure 4.1.
Cerdà's Plan for Barcelona:
Fragment of Cerdà's Plan
presenting block types and
orientation (top image).
Comparison between green
spaces and built spaces
(bottom image)

4.2.1.2. The Existing Setting

Although Cerdà's original plan engaged a balanced relationship between open space and liveable space, several changes to the plan were imposed after Cerdà's proposal due to a lack of infrastructure and remoteness of the new urban tissue from the old city. Moreover, political and investment opportunities transformed the original two-sided block with an open courtyard into a four-sided chamfered block with an enclosed courtyard, thus giving rise to the iconic Barcelona's eight-sided block. However, the decision to modify the original two-sided block completely disregarded Cerdà's intention to maintain a high percentage of open spaces and visual connectivity throughout the city (Busquets, 2004). By doing so, the green area/inhabitant ratio of Barcelona is currently recorded as 6.5m² per person, which is more than half the ratio recommended by the World Health Organization (Arroyo, 2009). However, in recent times, the main courtyard in many blocks throughout the city has been reclaimed by its inhabitants to re-introduce green areas and public buildings such as libraries (figure 4.2.).



Modifications to Cerdà's original plan has been in a continuous state of development, and the city itself is currently trying to adapt in an attempt to address diverse issues. Most prominently, Barcelona's driving factors of change are: the geographic relationship (Cornella mountains, Besòs river, Llobregat river and maritime front), the hierarchical and relational changes in specific areas such as Barcelona's future centre (Les Glories) and the rethinking of L'Eixample.

In an attempt to restore Cerdà's intent of a city that encompasses sustainable mobility, public space rehabilitation, biodiversity and green areas, accessibility, social cohesion and energetic self-sufficiency, the city has followed a strategy of restructuring the superblock in an attempt to create relationships between different blocks and between the block and the street (Ajuntament de Barcelona, 2013). However, due to the existing density of Barcelona, attempts at restructuring the Eixample are notably constrained to minor changes to the existing urban condition.

Figure 4.2.
Evolution of the Eixample
Block: The development of a
typical Eixample block from
its original design in 1859 to
modern day.

4.2.1.3. The Evolutionary Strategy for Barcelona

Cerda's initial plans attempted to provide a solution to a problem with multiple conflicting criteria (some of which were implemented at a later date). The primary conflicting criteria during the implementation of Cerda's plan was the requirement for the city to accommodate a high-density ratio yet maintain a high number of street-accessible green spaces. However, rather than generate a solution that accommodated both criteria, a trade-off strategy directed the city towards one that prioritised population density over green spaces.

Although unknown at the time, Barcelona's urban development was following a preference-based approach that found it necessary to "convert the task of finding multiple trade-off solutions in a multi-objective optimization (*problem*) to one of finding a single solution of a transformed single-objective optimization problem" (Deb, 2001, p. 7). As discussed in previous sections, the use of evolutionary population-based solvers empowers the possibility to modify, evaluate and select a set of candidate solutions per each iteration, rather than a single optimal solution. Such a process allows all objectives to be considered without the requisite of employing a trade-off strategy during the simulation. More importantly, it allows for the emergence of morphological variation of different solutions, each suitable for a specific function, thus, moving away from the homogeneity of 20th century urban planning strategies towards a more bottom-up approach of urban form.

4.2.2. Experiment Setup

The following experiments explore the relationship between the genes (the variables that are used to define the phenotype) and the body parts (the mode of differentiating between the different parts that makeup the phenotype). More importantly, the relationship of gene/body part to the fitness objectives being optimised for plays an equally important role in the simulation's development. Therefore, a clear definition of the genes, body part and fitness objectives, is necessary to establish how they relate to and regulate one another.

The experiments utilise Ildefon Cerda's unique Eixample block as the main component that comprises the 16-block superblock (*the phenotype*) onto which the solver will run. The experiment aims to generate an urban superblock that achieves an efficient courtyard relationship (by opening courtyards to one another through deleting the sides of adjacent blocks (figure 4.3.)), a high density ratio, a high ground solar exposure ratio (through utilising a single vector to represent the sun) and an increase in the size of courtyards (figure 4.4.).

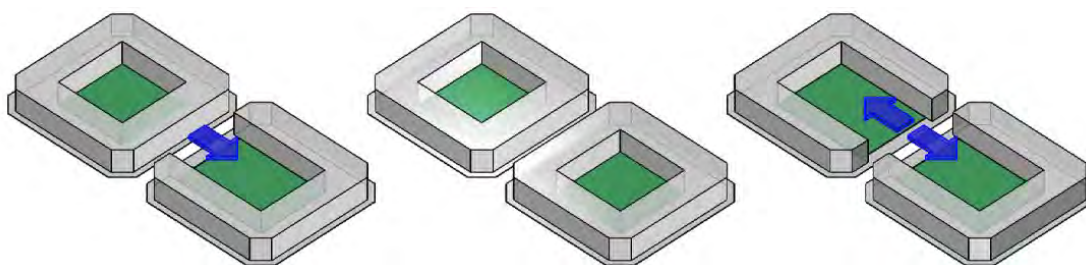
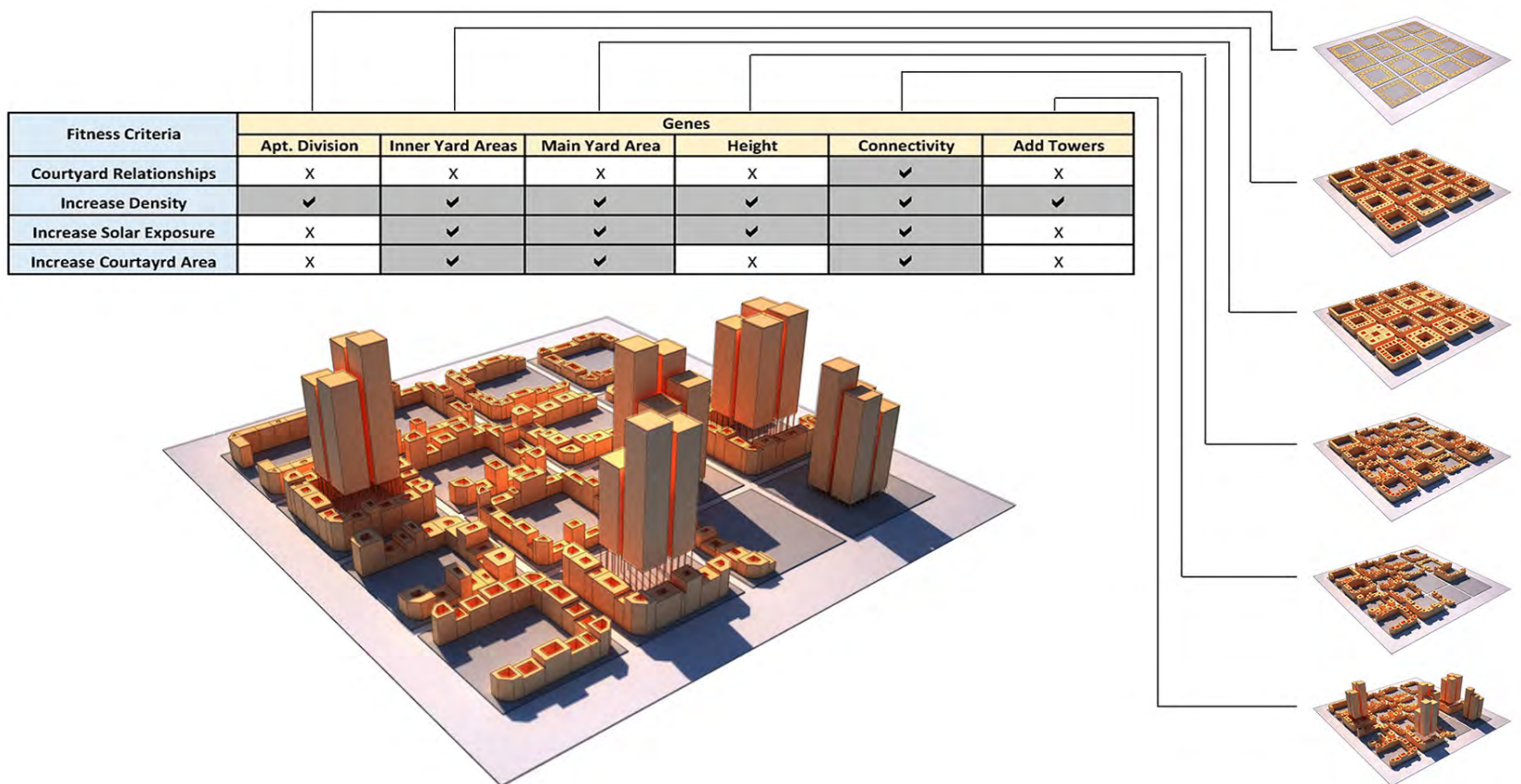


Figure 4.3.
Connectivity between Blocks:
The design problem is set up
to favour adjacent courtyards
that are accessible to one
another.

To accomplish this, the *gene pool* employed in the algorithmic setup transforms the phenotype’s morphology through modifications to courtyard size (main courtyards and inner courtyards), building heights, unit divisions and courtyard connectivity between adjacent blocks. Moreover, the genepool also allows for the emergence of towers, should the solver find it a viable solution to generate higher density ratios while simultaneously maintain large open areas. The following table and illustration summarise the formulation of the design problem and the relationship between the bodyplan, genepool and fitness objectives.

Goal	<i>Generate an urban superblock that addresses Barcelona’s current population density yet maintains Cerda’s original goals of incorporating more green space within the city and a greater homogeneity between the blocks that comprise the urban fabric.</i>
Objectives	<ul style="list-style-type: none">• <i>High population density</i>• <i>Greater block connectivity</i>• <i>Minimal overshadowing of open spaces</i>• <i>Sufficient Open Space</i>
Fitness Criteria	<ul style="list-style-type: none">• <i>Maximise Density within the superblock</i>• <i>Maximise connectivity between adjacent blocks</i>• <i>Maximise Courtyard Size</i>• <i>Maximise Solar Exposure on Ground Level</i>
Phenotype	<i>4x4 superblock comprised from the Eixample block</i>
Gene Pool	<ul style="list-style-type: none">• <i>Number of building units within the block</i>• <i>Size of main block courtyard</i>• <i>Size of inner unit courtyards</i>• <i>Number of floors per unit</i>• <i>Number of sides per block</i>• <i>Size of Towers</i>

Figure 4.4.
Design Problem – Experiment
1: Summary of the design
problem and description of
how the fitness objectives,
gene sequences and body
parts regulate each other.



Finally, the population size for the first two experiments is comprised from a generation size of 20 and a generation count of 50. This was primarily informed by the computational runtime of generating and evaluating each solution and the overall aim of comparatively analysing the data outputted through the application of single objective optimisation and multi objective optimisation.

4.2.3. Experiment 1A – Single Objective Optimisation

The first experiment combines the four objectives through remapping the fitness values associated with each solution to a domain from 0 to 1. This allows for the equal weighting between the four objectives thus allowing the algorithm to equally optimise for the 4 fitness criteria. To do this, the original domain of each fitness objective needs to be defined, which requires the calculation of the maximum and minimum achievable fitness values for each objective, thus allowing their remapping into the new domain. In simple design problems such as this one, the task of calculating the original numeric range for each objective is plausible, however, in more complex design problems, this task becomes more challenging due to the increasing number of variables in the design problem. Although one method to calculating the numeric range of the fitness objectives in complex design problems would be to run the evolutionary algorithm for each objective independently until the optimal solution is found, thus highlighting the maximum and minimum fitness values, this approach may also fail when applied to complex problems.

*Figure 4.5.
Sample of Evolved Phenotypes
generated by the simulation.*

4.2.3.1. Outcome

Generation 20



Generation 40

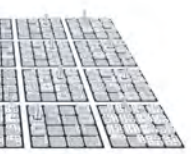


Generation 50





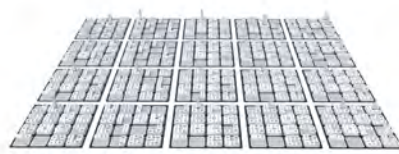
Figure 4.6.
All phenotypes generated by
the simulation.



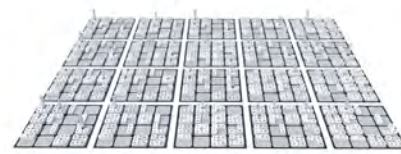
Generation 4



Generation 5



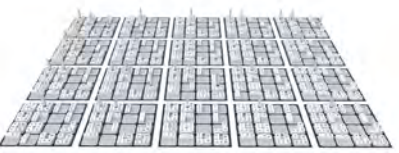
Generation 6



Generation 7



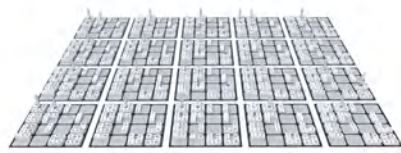
Generation 11



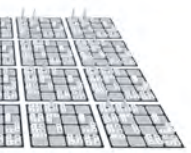
Generation 12



Generation 13



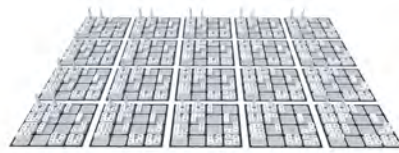
Generation 14



Generation 18



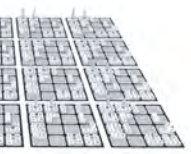
Generation 19



Generation 20



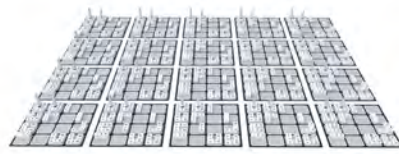
Generation 21



Generation 25



Generation 26



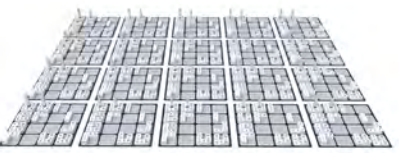
Generation 27



Generation 28



Generation 32



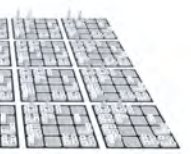
Generation 33



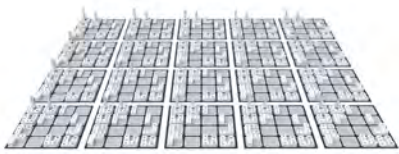
Generation 34



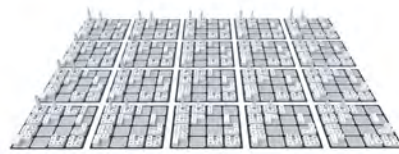
Generation 35



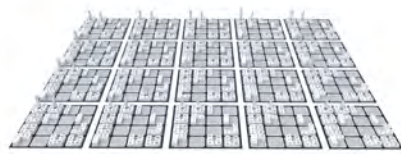
Generation 39



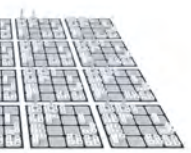
Generation 40



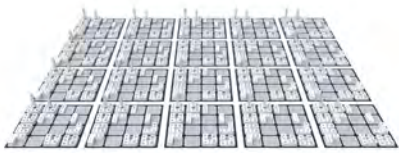
Generation 41



Generation 42



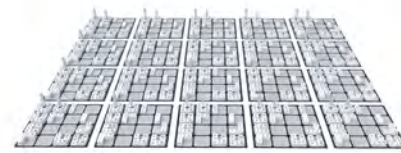
Generation 46



Generation 47



Generation 48



Generation 49

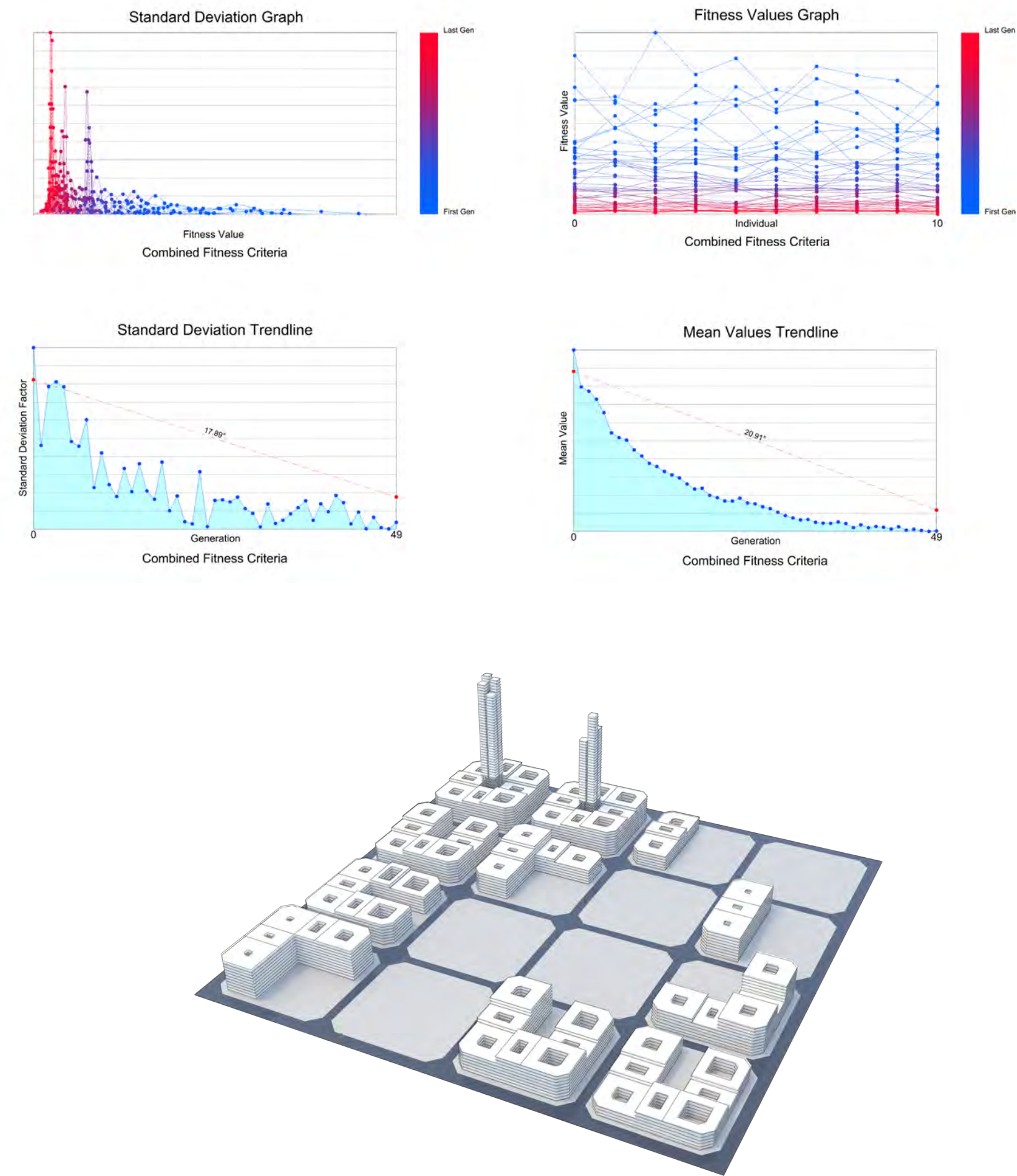


Figure 4.7.
Statistical analysis of the
simulation's output.

Figure 4.8.
The phenotype that the
simulation converged towards.

4.2.3.2. Analysis

As expected with a single objective optimisation approach, the population evolved towards a single 'optimal' solution. Where the earlier generations contained some degree of variation between the phenotypes, by the end of the simulation, the entire generation was comprised from the same solution with very little variation among the generation (figures 4.5. and 4.6.). Moreover, as the four objectives were weighted and optimised for equally, the solver optimised towards a solution that was the mean fitness for the four objectives, this is also to be expected from a weighted single objective optimisation approach (it must be clarified that this is not always the case, at times, the formulation of the design problem will drive the algorithm to favour some objectives over others, despite them being weighted equally) (figure 4.7.).

The converged phenotype displays morphological characteristics that have positively responded to the environmental conditions defined within the simulation (figure 4.8.). Primarily through the interplay between density and open space and the attempt to maximise solar exposure on ground level. In the former, the simulation favoured a phenotype that maximised the heights of the perimeter blocks within the superblock while simultaneously reducing the area of the main courtyard within each block (consequently minimising the number of towers that have emerged within the superblock). Additionally, the area of the inner courtyard within each block has been reduced in an attempt to further maximise the density. In doing so, the *solar exposure fitness objective* worked in unison with the *courtyard relationship fitness objective* to counteract the simulation's convergence towards a phenotype that exhibits increased density values by completely removing blocks in a diagonal pattern within the superblock. The diagonal directionality of the open spaces within the superblock is in response to the direction of the solar vector that has been defined in the design problem, signifying the solver's positive reaction to the environmental condition driving the evolutionary simulation ([Animation 1](#)).

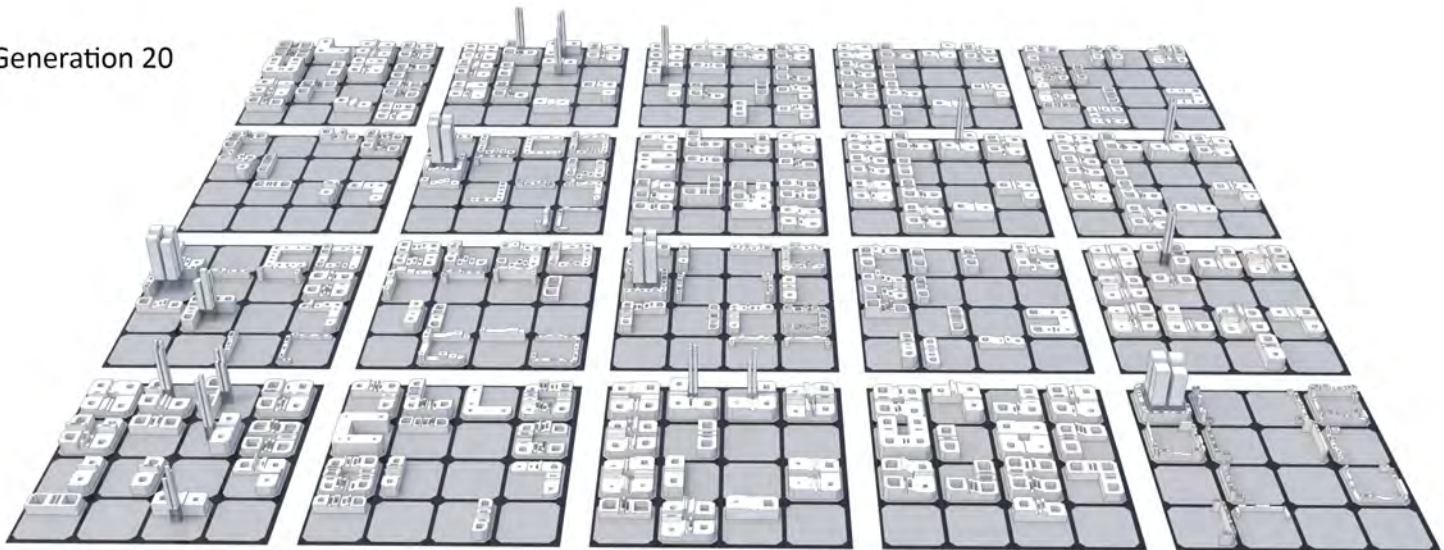
4.2.4. Experiment 1B – Multi-Objective Optimisation

Contrary to single objective optimisation, the use of population-based algorithms in multi-objective optimisation allows for the possibility to modify, evaluate and select a set of candidate solutions per each iteration rather than a single solution. Thus avoiding the necessity for the solver to combine multiple objectives into a single objective. Therefore, experiment 1B expands on the previous experiment by translating it from a single objective problem into one comprised from multiple objectives. In doing so, the simulation optimises for the same 4 objectives through their independent evaluation according to their respective fitness criteria, thus signifying the variation within the pareto front rather than the convergence of the population towards a single solution.

Figure 4.9.
Sample of Evolved Phenotypes
generated by the simulation.

4.2.4.1. Outcome

Generation 20



Generation 40



Generation 50





Figure 4.9a.
Generation 55: The final
generation generated by the
simulation





Figure 4.9a.
Generation 55: The final
generation generated by the
simulation



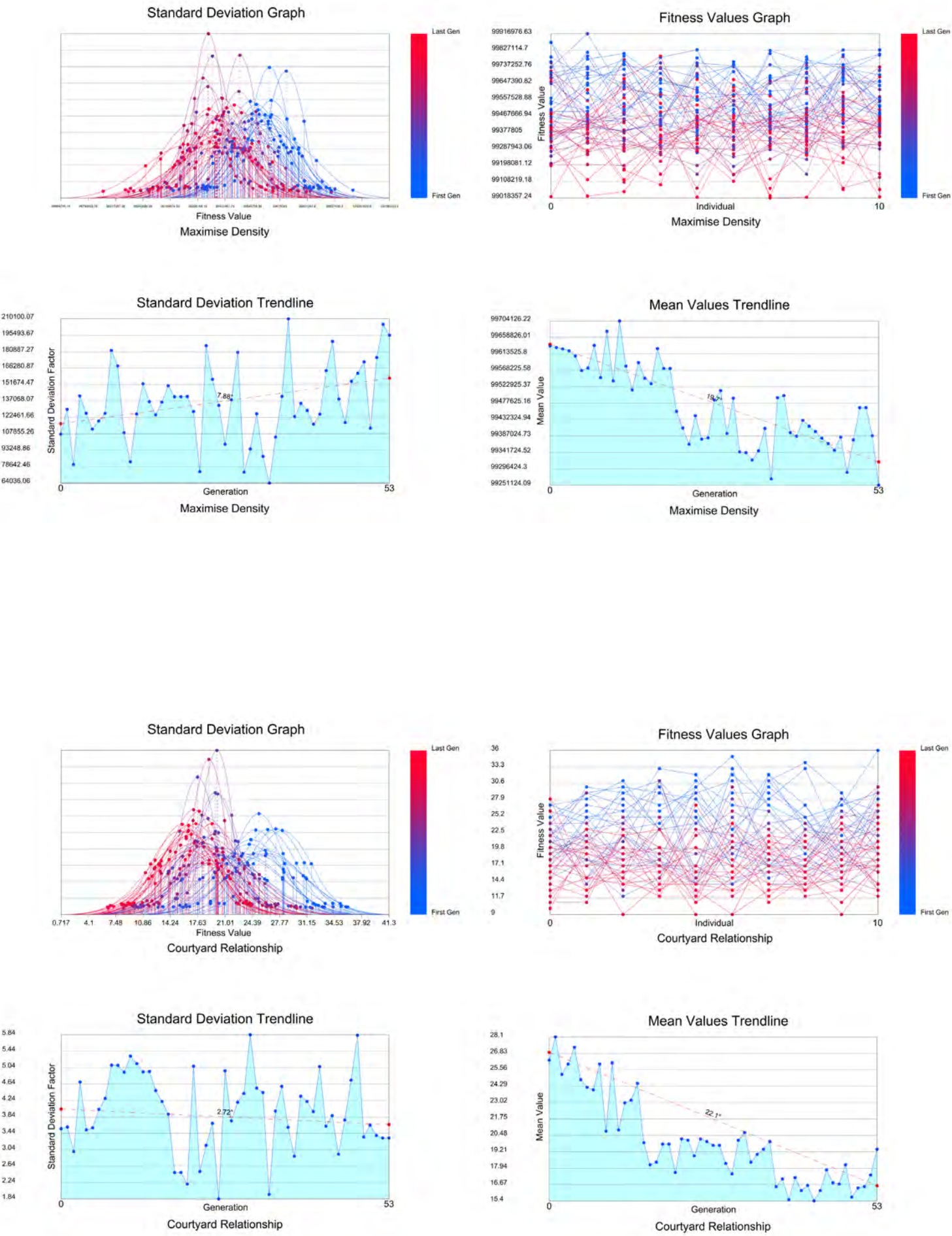
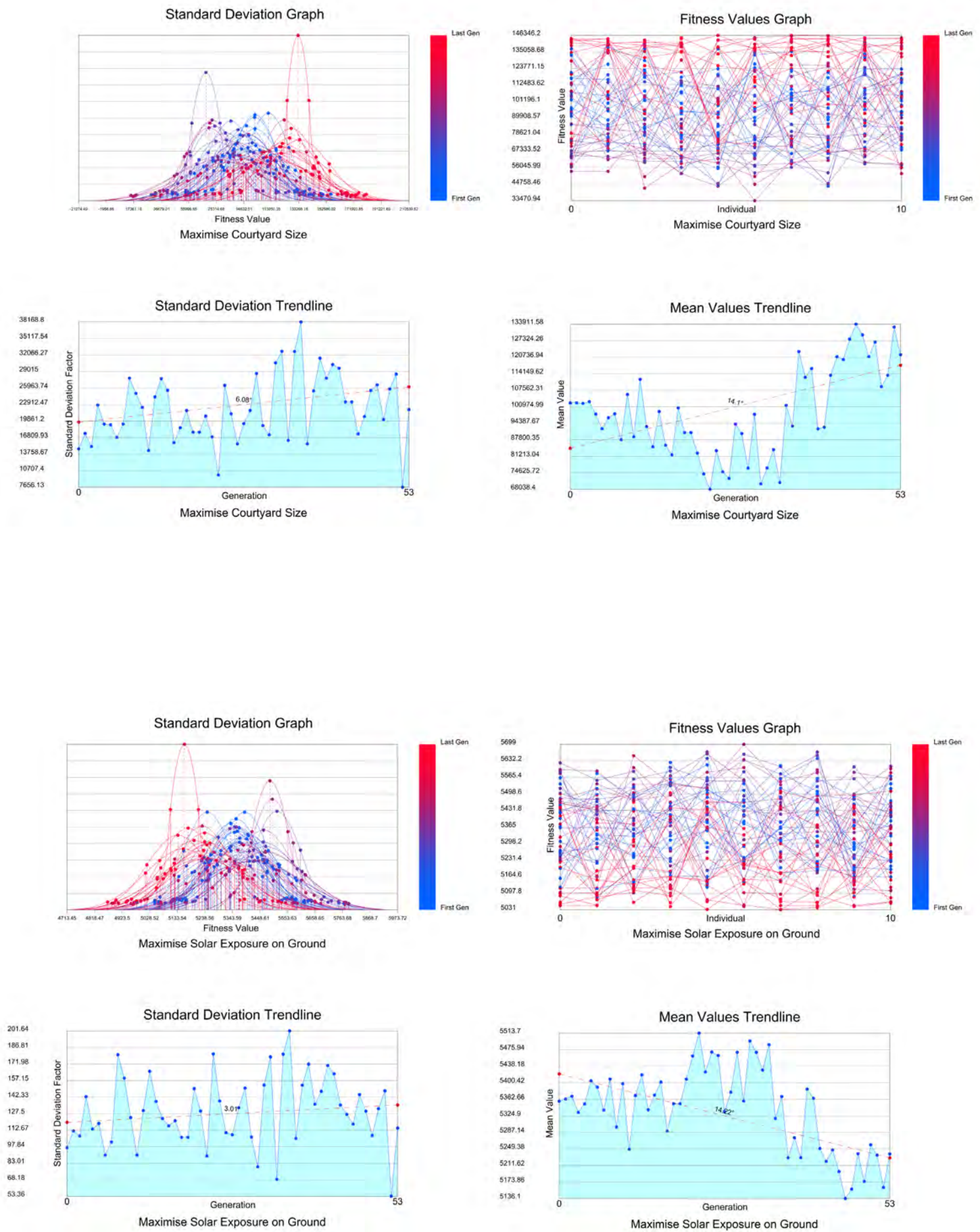


Figure 4.10.
Statistical analysis of the
simulation's output.



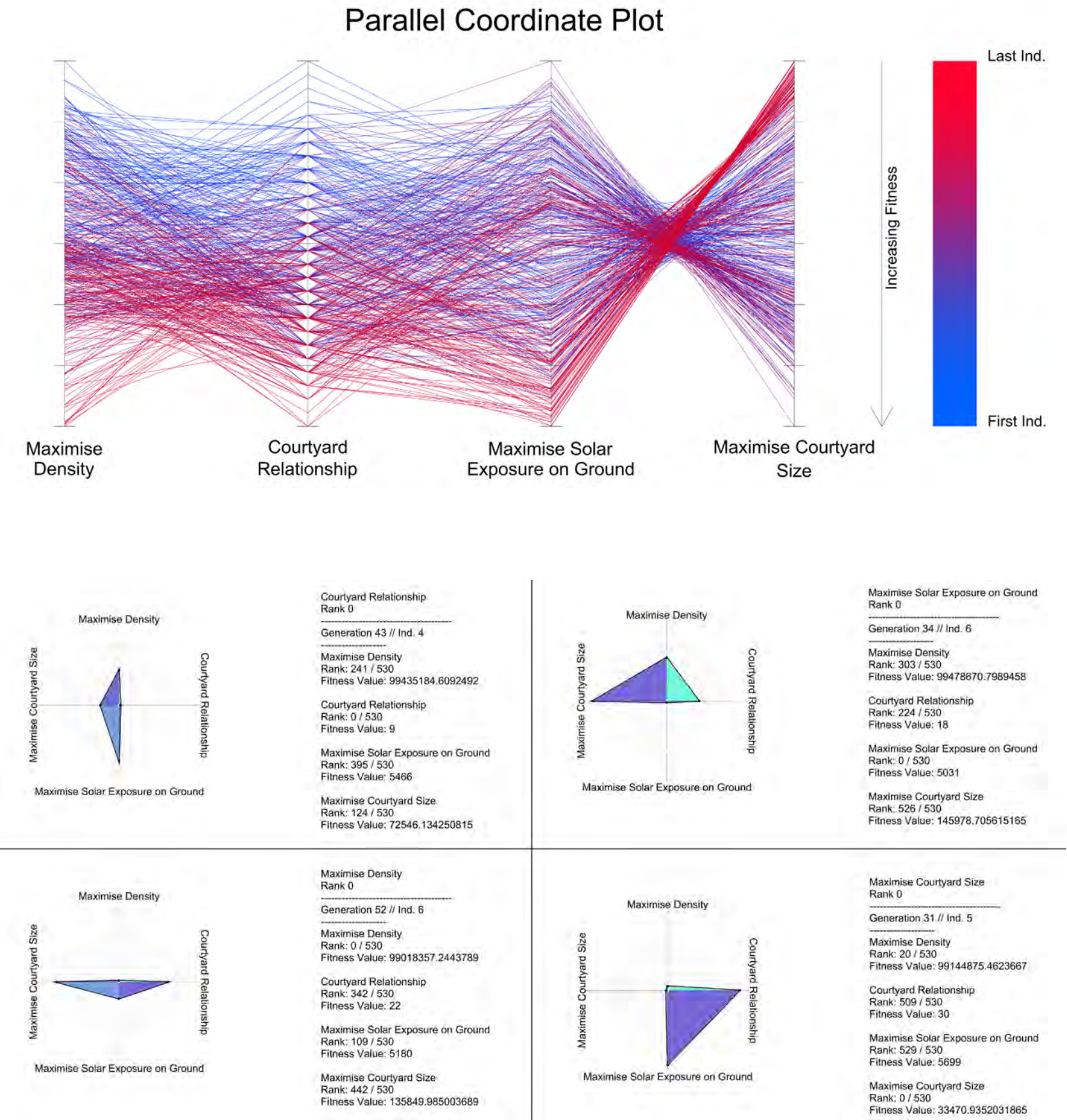


Figure 4.11.
Analysis through the Parallel
Coordinate Plot and the
selection of the fittest solution
for each objective through the
Diamond Fitness Chart.

4.2.4.2. Analysis

Contrary to the single objective experiment, the analysis of a multi objective experiment requires the delineation and graphical representation of each fitness objective independently. This highlights the necessity for evaluating the data associated with each objective in relation to one another and not in isolation. In doing so, it allows for a comprehensive understanding of how the objectives impact one another, and whether possible emergent patterns between the objectives can be observed. The analysis of the numerical data generated by the evolutionary solver highlights the following (figures 4.10. and 4.11.):

- The standard deviation (and consequently the variance levels) throughout the population remains relatively high, indicating that the simulation is capable of exploring the fitness landscape throughout the simulation run without converging towards a local optimum.
- Despite the above, the standard deviation values fluctuate multiple times throughout the simulation's run for all 4 objectives. This indicates that in multiple instances throughout the simulation's runtime, mutations applied to some individuals in the population generate extreme solutions, which indicates a noisy fitness landscape comprised from multiple peaks that are in close proximity to one another.
- The mean fitness value for 3 of the fitness objectives (density, courtyard relationship and ground solar exposure) decrease incrementally throughout the simulation run (i.e get fitter). In contrast, the mean fitness for the fourth objective, *courtyard size*, gets better for the first half of the simulation, and then incrementally worsens in the second half of the simulation (from generation 34 onwards). An analysis of the morphological characteristics of the solutions in the population at generation 40 indicates that it is around this point in the simulation where towers began to emerge in high numbers. This indicates that the simulation navigated the fitness landscape towards a peak that allowed it to optimise for the first three objectives, despite the fourth objective getting weaker.
- An analysis of the parallel coordinate plot indicates that the most conflicting criteria are the *maximise courtyard size* and *maximise solar exposure on ground*. This seems to contradict what was initially anticipated, which was for these two criteria to complement one another (as increasing courtyard size would consequently allow for more open space to receive sunlight). However, this is explained through an analysis of the design problem; towers were allowed to emerge when the courtyard area increased beyond a specified threshold, which in turn increased overshadowing on surrounding courtyards, thus explaining the pattern observed in the parallel coordinate plot.
- The parallel coordinate plot also highlights the fact that there is no single optimal solution as there is no solution whose curve lies on the x-axis (i.e. a solution that is fittest for each fitness criteria).

- As anticipated, the fittest solutions for each criterion are not located in the final generation. The diamond fitness charts highlight the fittest solution for each criterion and its location in the population. For one of the criteria, the fittest solution emerged as early as the 31st generation (maximise courtyard size); confirming the necessity for analysing the complete population set and not only the final generation of the simulation.

The morphological analysis of the population presents a clear evolution of solutions that were initially low rise with very little towers towards solutions comprised from a combination of towers and open space. More importantly, within the latest generations, there are a small number of solutions that are comprised from low rise blocks with much smaller towers. This confirms that throughout the simulation's run, even though the solver seemed to evolve towards a specific form, it still preserved within the solution set of the latest generations an alternative, highly varied morphology. The main benefit of this is that within each generation, these 'extreme' solutions give the simulation the flexibility to explore more of the fitness landscape without getting 'stuck' in a local optimum, thus allowing it to adapt to a fitness landscape that is defined by a complex design problem that cannot be simplified by the user (figure 4.9.).

4.2.5. Conclusions

The two experiments presented above highlight the difference in output between single objective and multi-objective optimisation problems. Where the former resulted in the simulation converging towards a single 'optimal' solution (the typologist), the latter maintained a degree of variation within each generation (the populationist), while simultaneously evolving the population towards shared morphological characteristics. Additionally, although the design problems for both experiments were expressed through a regulation between genes, body parts and fitness objectives; the effect of this relationship was significantly reduced in experiment 1A, as by combining the fitness objectives in one, the regulation of the phenotype became less impactful. This was primarily due to the fact that regulating for one objective had the same impact on all other objectives. Whereas in experiment 1B, the regulation of genes and body parts to the fitness objectives were independent of one another, thus allowing for the simulation to 'favour' the regulation of some genes as opposed to others.

However, variation within the population may be also directed through the parameters of the evolutionary algorithm itself. Although the solver presents itself as a 'black box', in which the user plugs in the design problem and extracts the evolved solutions without the necessity to modify the evolutionary algorithm itself; there are limited parameters that the user *can* modify in the aim of directing the algorithm towards efficiently navigating the fitness landscape. In short, modifying the parameters aim to direct the simulation towards convergence or divergence of its population from local/global peaks within the landscape. The parameters that can be modified are the following (refer to the glossary (Chapter 9) for detailed definitions); *Elitism*, *Mutation Probability*, *Mutation Rate*, *Crossover Rate*.

The effectiveness of modifying the above parameters on the simulation's efficiency in evolving a fit and diverse population is not assured; this is due to the following:

- The parameters can be modified only when the simulation is not running; therefore, the user must first run the simulation, analyse the output and modify the parameters according to how much exploitation or exploration of the fitness landscape has been observed. The disadvantage of this approach is that the impact of the parameters modifications can only be observed intermittently and through multiple runs of the simulation. In cases where the design problem is complex (and thus associated with long calculation times), this approach is cumbersome to the user. This is partly due to the following point;
- The user cannot confidently claim whether changing the parameters is beneficial for the algorithmic run, although the parameters can be changed to 'push' the simulation towards a specific direction, this is coupled with a degree of uncertainty on whether the changes made are sufficient and/or correct in addressing the algorithmic problems observed by the user.
- The parameters control how the simulation is navigating the fitness landscape but has no effect on the shape of the landscape itself. Therefore, the user can modify the parameters many times without yielding beneficial results due to the landscape itself (which is derived from the formulation of the design problem) being too complex.

In this context, the evolutionary simulation's efficiency in navigating the fitness landscape should be addressed through the evaluation and reformulation of the design problem rather than the modification of the parameters driving the evolutionary algorithm. This is not to imply that modifying the solver parameters is not beneficial to an efficient navigation of the fitness landscape; to do so however, the parameter settings must be dictated by the size of the population in the conducted experiment so as to ensure a balanced exploration and exploitation of the fitness landscape is achieved. This leads to the formulation of the design problem in the following experiment (experiment 2), where the population size is increased, and the algorithms parameters are modified accordingly.

4.3. Experiment 2 - Barcelona

4.3.1. Ambition

Following the experiments conducted above, in which the application of single objective optimisation and multi-objective optimisation for the same design problem were analysed, the design problem in the following experiment was reformulated in order to examine the application of an evolutionary simulation comprised from a much larger population size in a multi objective design problem. Experiment 2 also examines the methods for *selection* of a group of solutions from the evolved population through an analysis of the relative difference between each solution's fitness values and a comparative analysis of their average fitness rank.

The objective of generating a solution set that addresses Barcelona's current density and Cerda's original intention of open space within the urban fabric remains the same. However, following the experiments conducted above, the design problem was reformulated in order to provide a more balanced optimisation of the four fitness criteria while simultaneously maintaining sufficient variation within each generation outputted by the simulation. This was achieved by revisiting the fitness objectives and the genepool defined in the previous experiments.

4.3.2. Experiment Setup

The fitness objectives of the previous experiment favoured open space over density. Maximising *Connectivity*, *Courtyard Area* and *Ground Floor Exposure* would direct the simulation towards larger amounts of open space despite the fourth objective aiming to maximise *Density* (which would direct the simulation towards deeper and higher buildings and smaller courtyards). Although this was counteracted through the emergence of towers, which allowed for the simulation to counteract the '*3 against 1*' relationship between the fitness criteria; disallowing the emergence of towers (discussed in the following section) would require a more balanced relationship between the four fitness objectives.

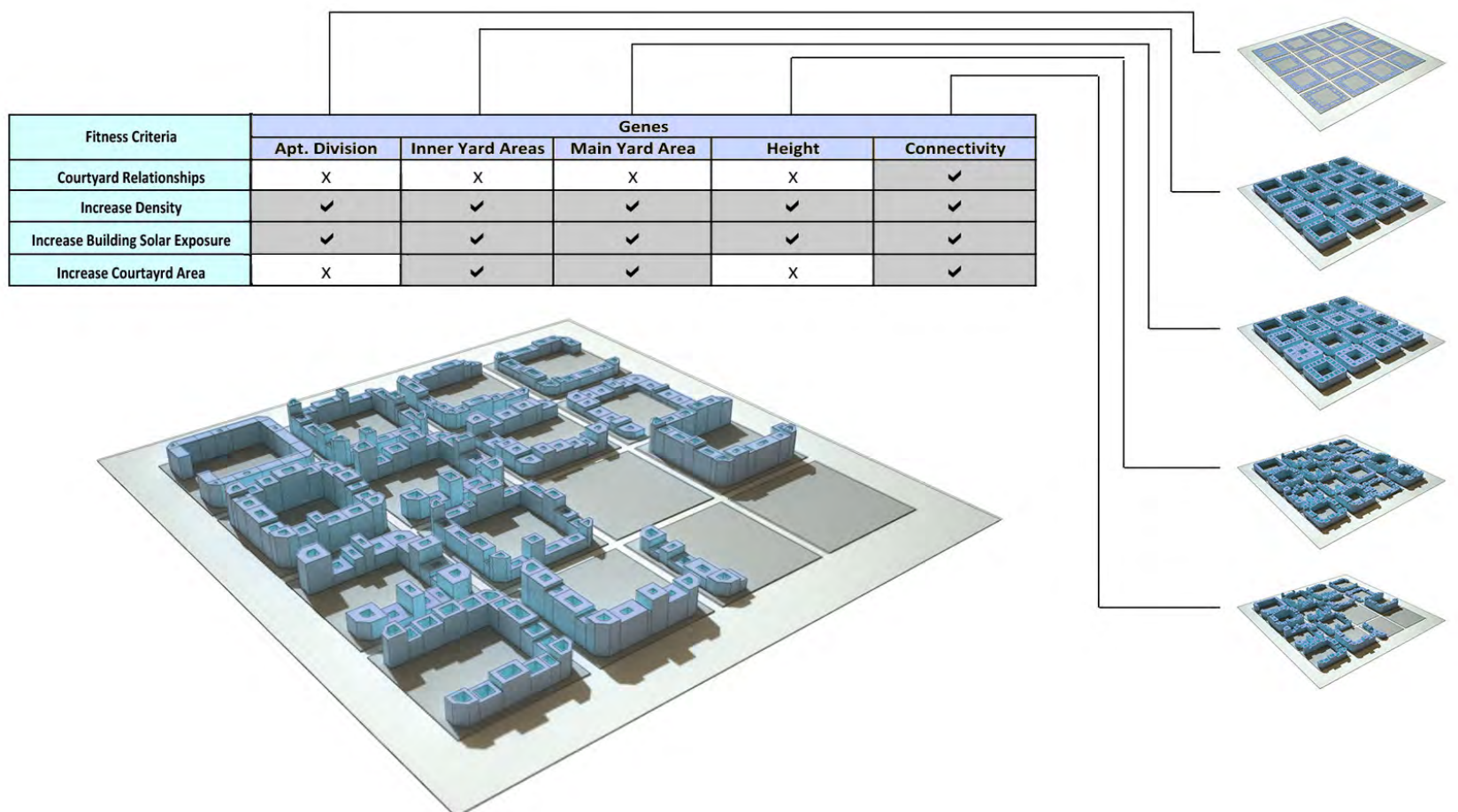
Connectivity is essential to ensure the blocks 'communicate' with one another within the same superblock, and *Density* is equally important to ensure the simulation optimises for block density ratios that may be comparable to Barcelona's existing density values. The harmonious relationship between maximising *Courtyard Areas* and maximising *Ground Solar Exposure* indicates that one of these two criteria can be replaced with an objective that favours maximising density (as courtyard connectivity favours open space). Therefore, rather than calculating solar gain on the ground floor, the design problem was reformulated so as to perform the solar calculation on the buildings within the superblock, thus by maximising this value, the simulation would ideally aim to maximise the area of the building envelope of each block, which in turn would increase the density values for the superblock.

4.3.2.1. Gene Pool

To establish a more comparable analysis between the generated solutions and the superblock proposed by Cerda and the existing superblock, the genepool was revised so as to include variables that are more closely related to the morphological characteristics currently present in the Eixample block. As such, the genes present in the previous experiments that allowed for the emergence of towers were removed from the reformulated experiment setup. In doing so, the regulation between genes and fitness objectives and body parts was additionally modified (figure 4.12.).

Goal	<i>Generate an urban superblock that addresses Barcelona's current population density yet maintains Cerda's original goals of incorporating more green space within the city and a greater homogeneity between the blocks that comprise the urban fabric.</i>
Objectives	<ul style="list-style-type: none"> • <i>High population density</i> • <i>Greater block connectivity</i> • <i>Greater solar gain for each block</i> • <i>Sufficient Open Space</i>
Fitness Criteria	<ul style="list-style-type: none"> • <i>Maximise Density within the superblock</i> • <i>Maximise connectivity between adjacent blocks</i> • <i>Maximise Courtyard Size</i> • <i>Maximise Solar Exposure on Buildings</i>
Phenotype	<i>4x4 superblock comprised from the Eixample block</i>
Gene Pool	<ul style="list-style-type: none"> • <i>Number of building units within the block</i> • <i>Size of main block courtyard</i> • <i>Size of inner unit courtyards</i> • <i>Number of floors per unit</i> • <i>Number of sides per block</i>

Figure 4.12.
Design Problem – Experiment
2: Summary of the design
problem and description of
how the fitness objectives,
gene sequences and body
parts regulate each other.



Moreover, and in line with the intention of generating a comparable data set, the domains of each of the genes incorporated within the design problem were defined in close proximity to a typical Eixample block. These were set as follows:

Gene	Domain	Notes
Building Division	$2 \text{ units} \leq X \leq 6 \text{ units}$	Each side of the block can be divided to any number of units between 2 and 6
Inner Yard Areas	$30\% \leq X \leq 70\%$	Inner courtyards are scaled down from the footprint of the building division it belongs to
Main Yard Area	$20\% \leq X \leq 120\%$	The main courtyard is scaled down or up from the courtyard size of a typical Eixample block
Building Height (no. of levels)	$2 \text{ levels} \leq X \leq 9 \text{ levels}$	Each building division can be allocated with any number of floors between 2 and 9
Connectivity	$0 \text{ sides} \leq X \leq 4 \text{ sides}$	Each block can be comprised from any number of sides that range from 0 (no block at all) to 4 (completely enclosed block)

4.3.2.2. Solver Parameters:

Through increasing the generation size from 20 to 100, and the generation count from 50 to 100, the simulation was capable of evolving a population size comprised from 10,000 solutions. Additionally, and in progressing from experiment 1, the algorithm's parameters were modified according to the large population size as to direct the solver towards a balanced exploration and exploitation of the fitness landscape. To achieve this, the mutation rate and probability were increased to allow for more variation to emerge within each generation. The parameters were defined as follows:

Elitism	50%
Mutation Probability	33%
Mutation Rate	66%
Crossover Rate	80%

4.3.3. Outcome

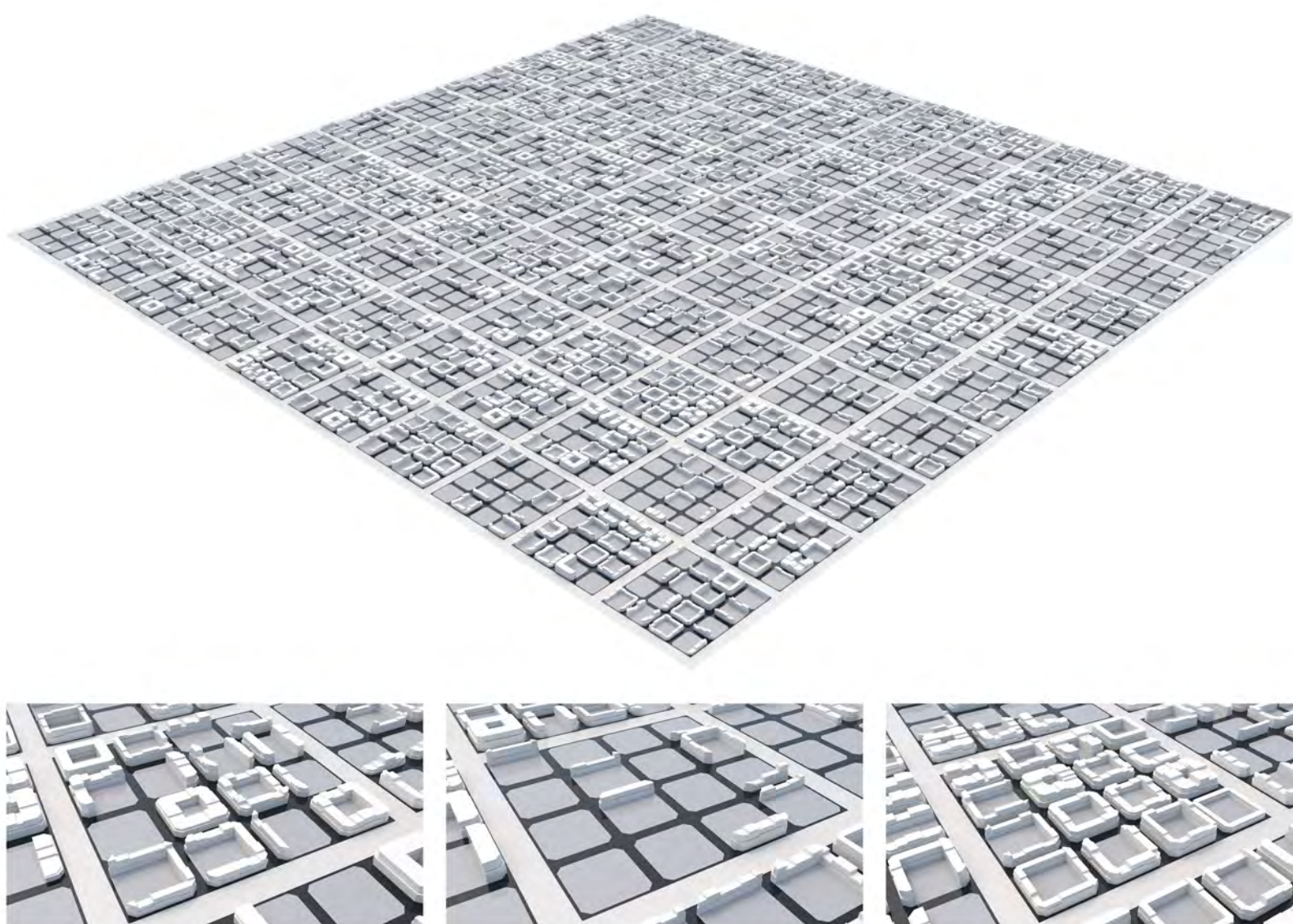


Figure 4.13.
Phenotypes evolved by the simulation: The final generation of the population with a detailed view of the variation between different superblocks within the same generation.

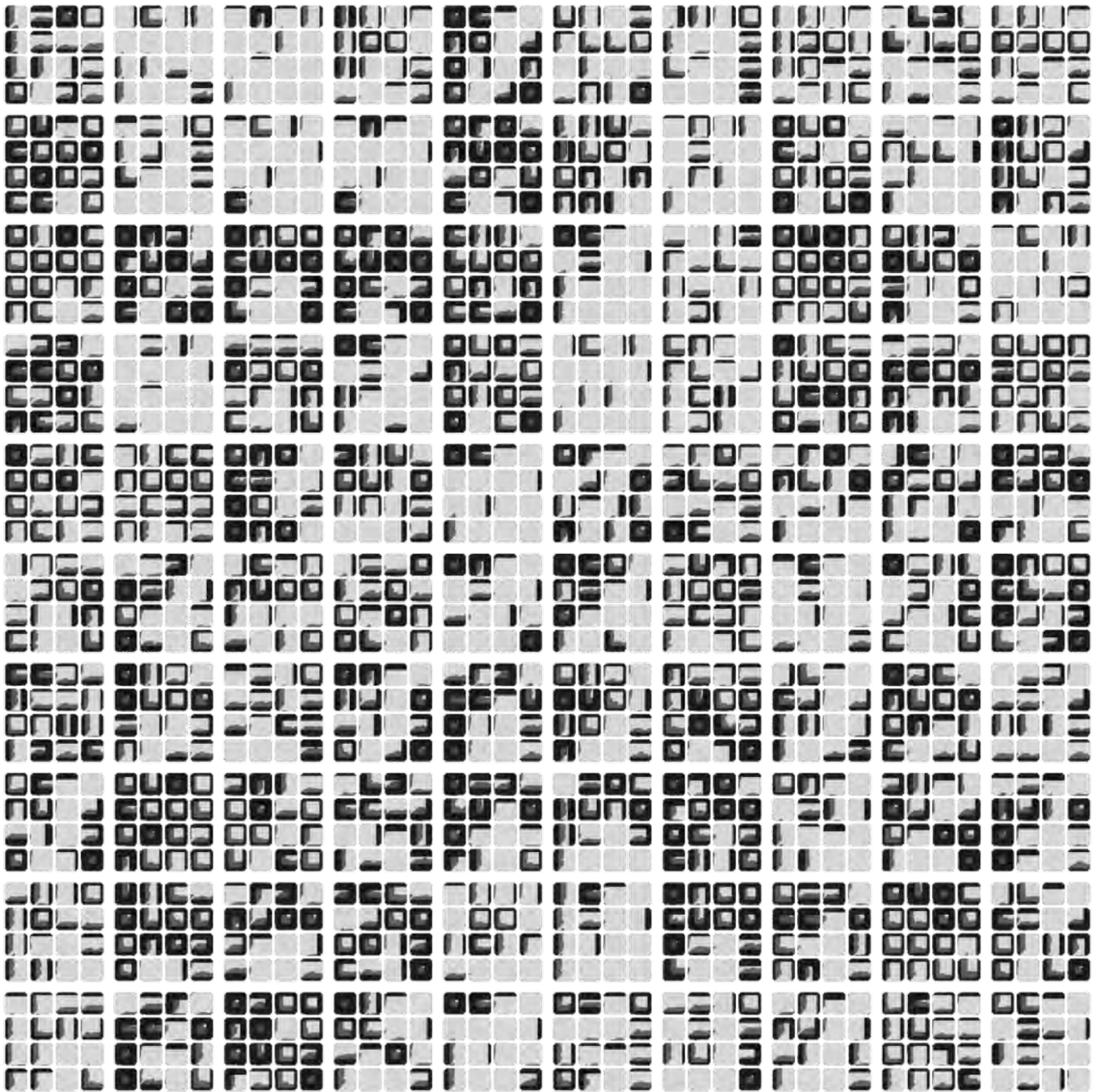


Figure 4.14.
Shadow Analysis of Final
Generation.

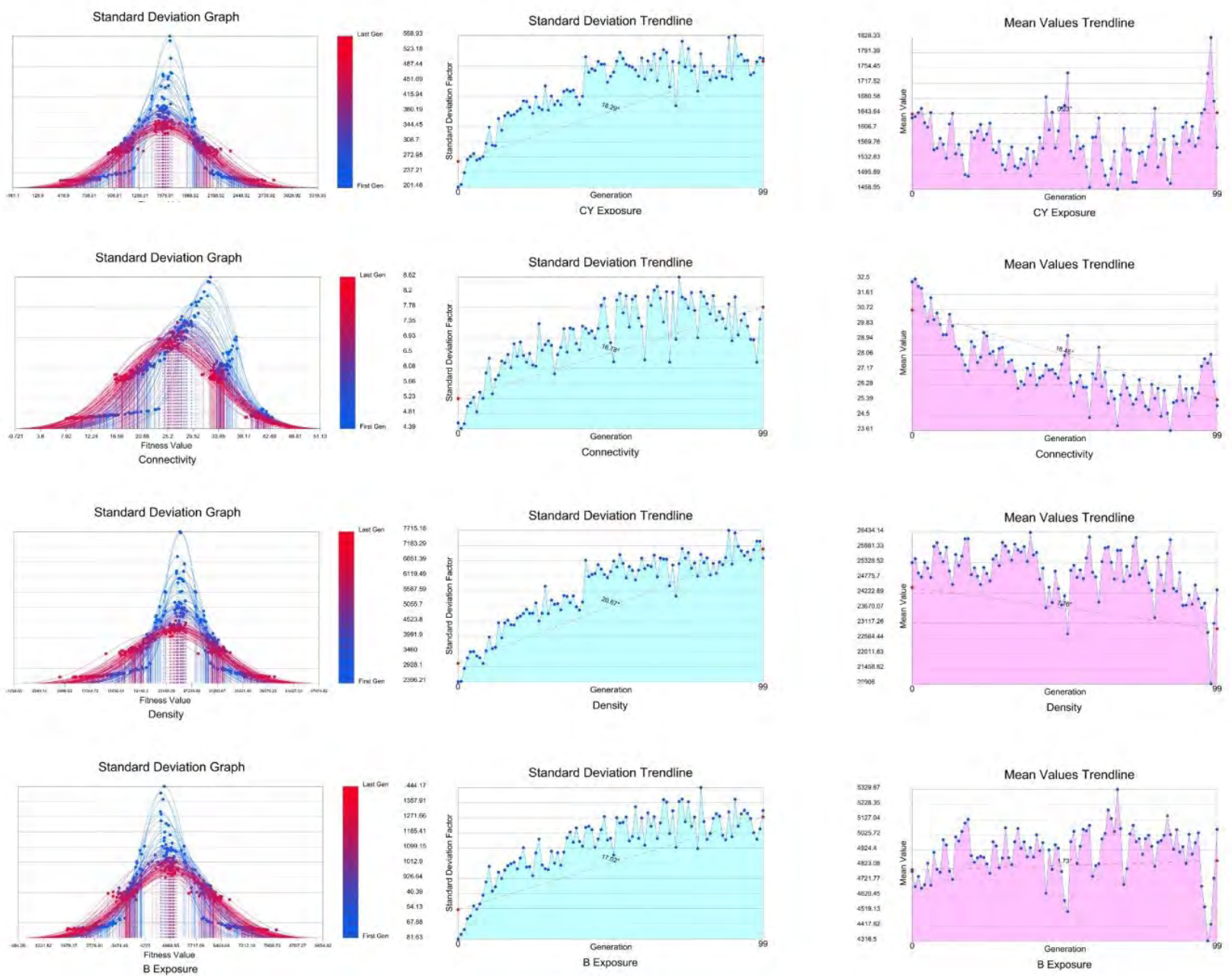


Figure 4.15.
Statistical analysis of the
simulation's output.

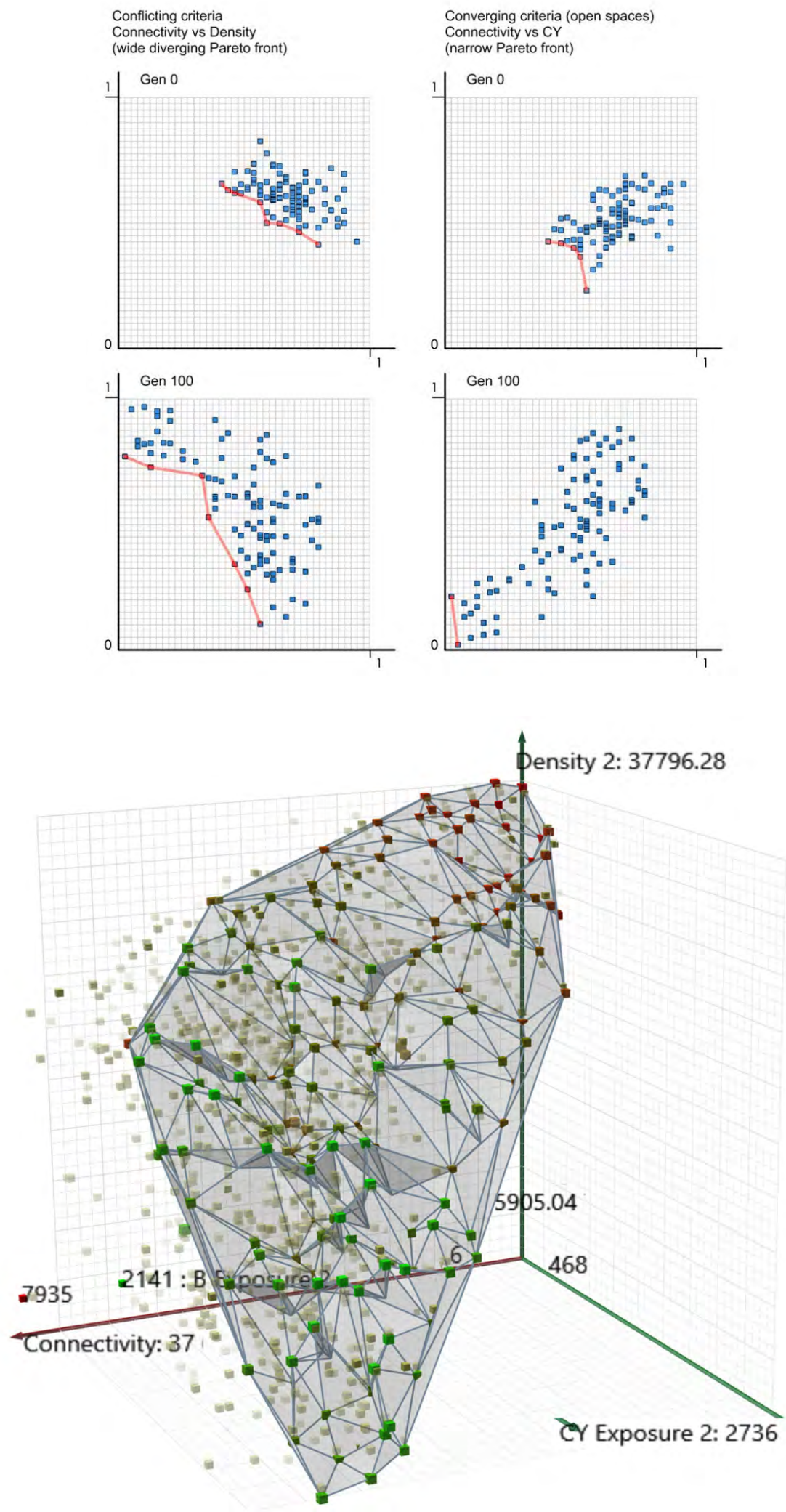


Figure 4.16.
The objective Space: A comparative analysis of the different fitness objectives through the distribution of solutions within the objective space

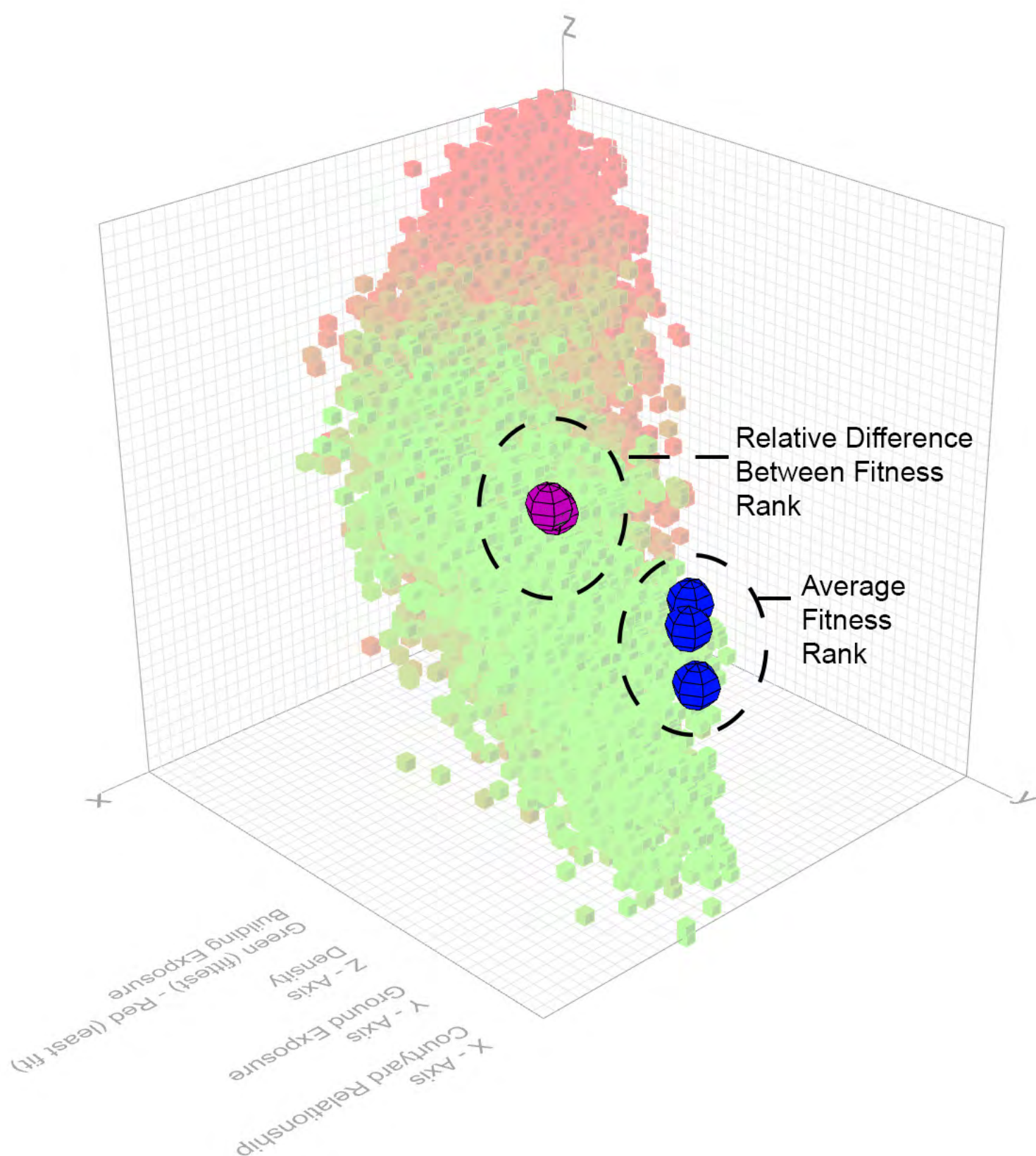


Figure 4.17.
The location and relationship
of the selected solutions to the
rest of the population in the
Objective Space.

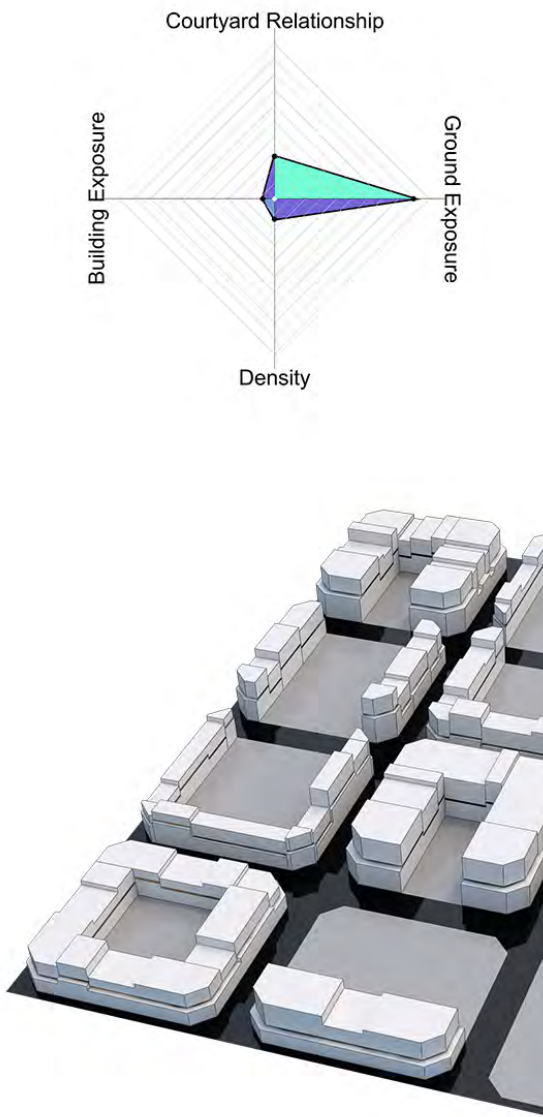
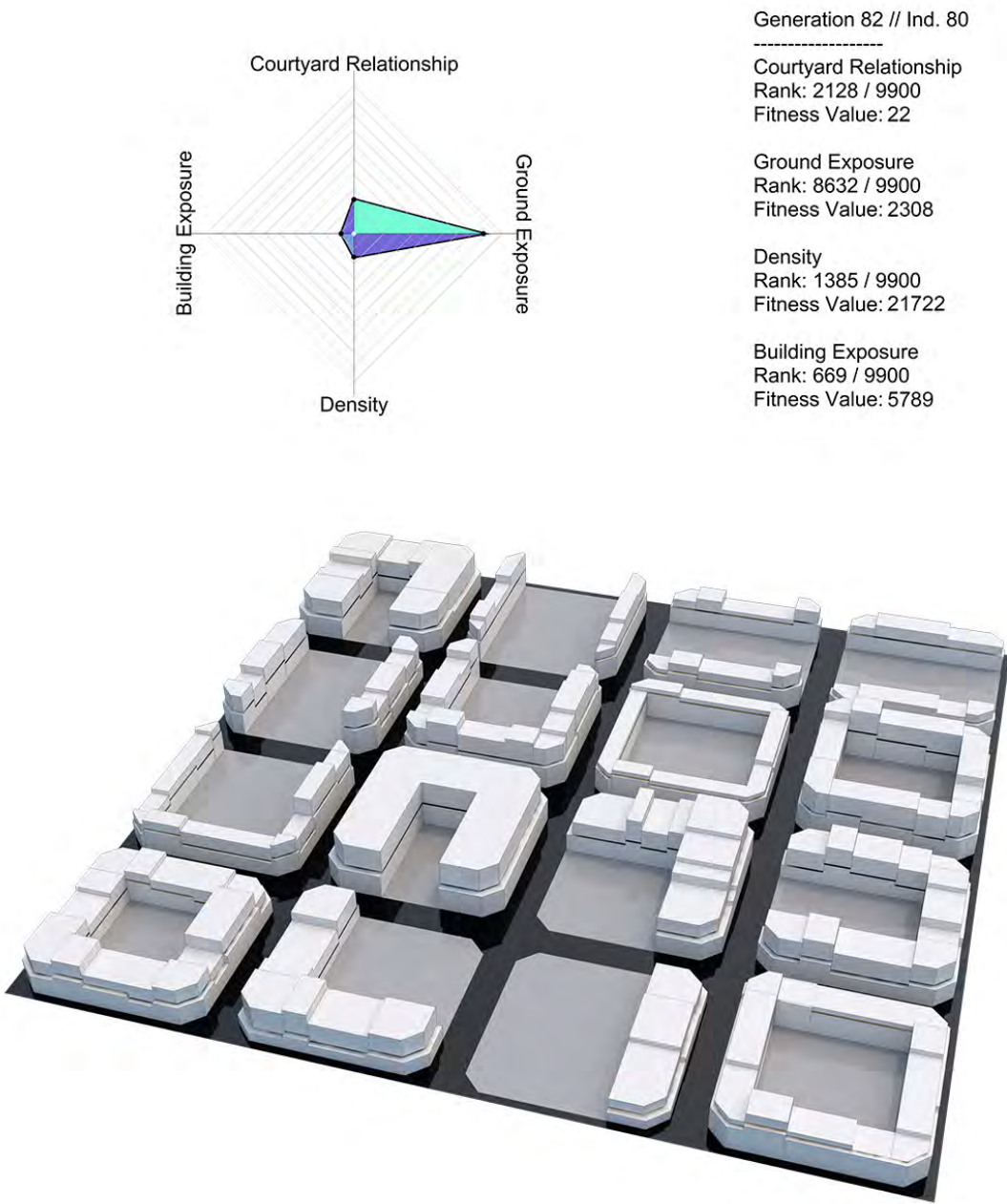


Figure 4.19.
The fittest 3 phenotypes
selected according to the mean
fitness ranking extracted from
the analysis of the Parallel
Coordinate Plot.

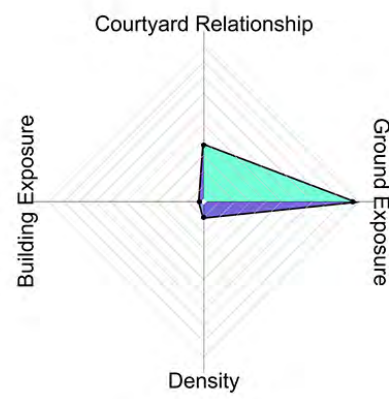
Generation 96 // Ind. 66

Courtyard Relationship
Rank: 2551 / 9900
Fitness Value: 27

Ground Exposure
Rank: 8849 / 9900
Fitness Value: 2259

Density
Rank: 1122 / 9900
Fitness Value: 22661

Building Exposure
Rank: 553 / 9900
Fitness Value: 5869



Generation 94 // Ind. 64

Courtyard Relationship
Rank: 3485 / 9900
Fitness Value: 24

Ground Exposure
Rank: 9511 / 9900
Fitness Value: 2048

Density
Rank: 809 / 9900
Fitness Value: 23938

Building Exposure
Rank: 72 / 9900
Fitness Value: 6558



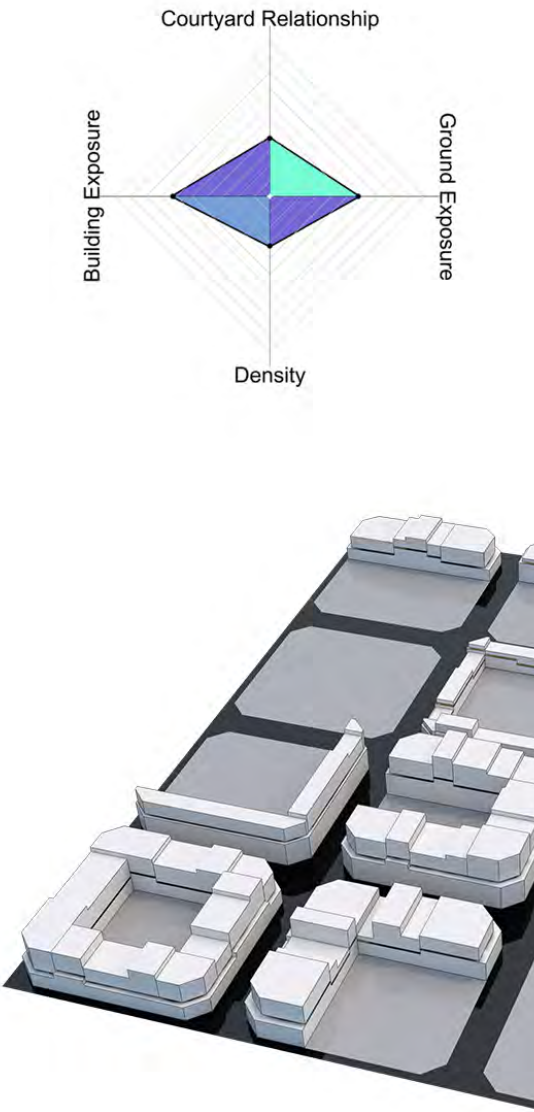
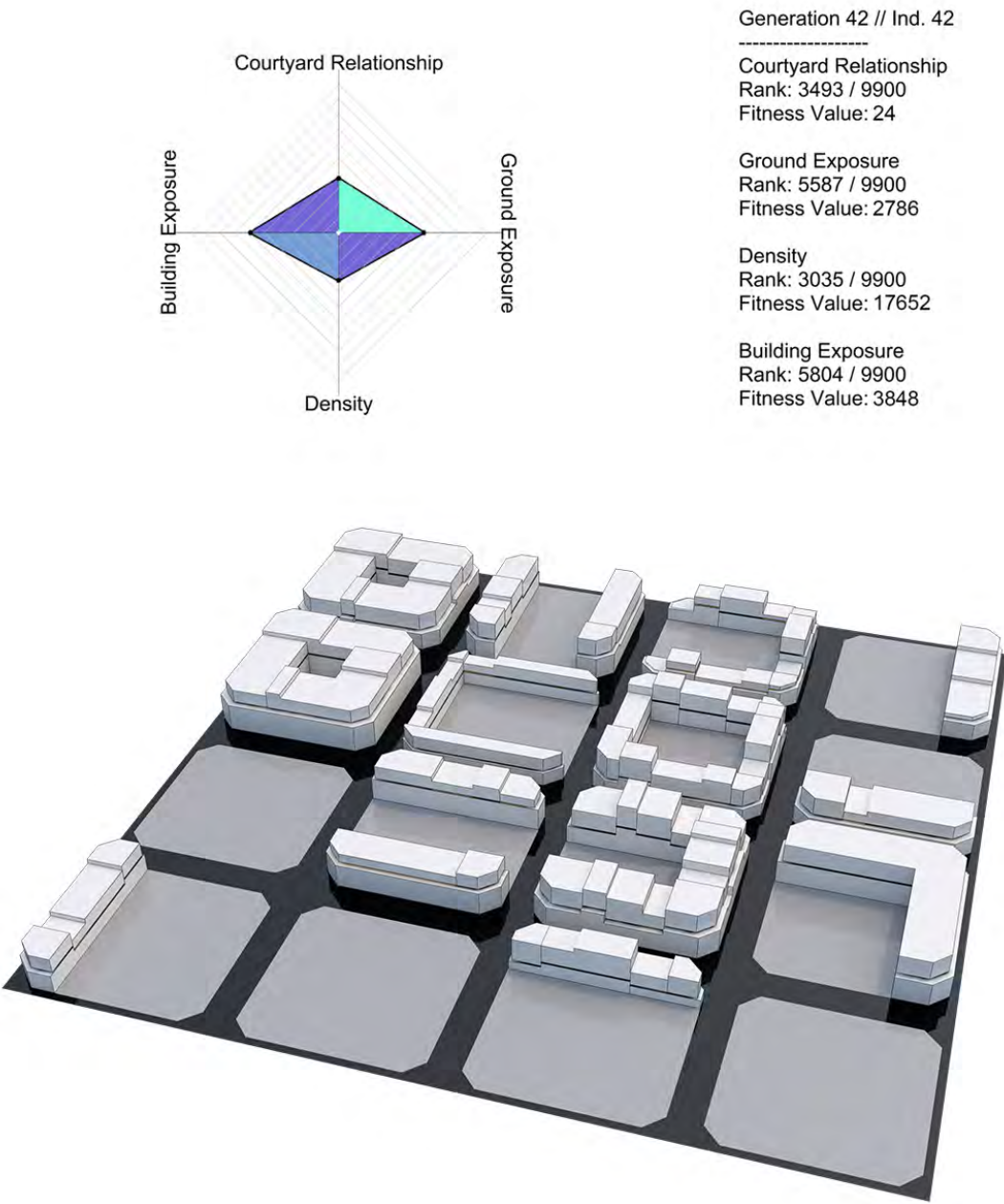


Figure 4.19.
The fittest 3 phenotypes
selected according to the
relative difference ranking
extracted from the analysis of
the Parallel Coordinate Plot.

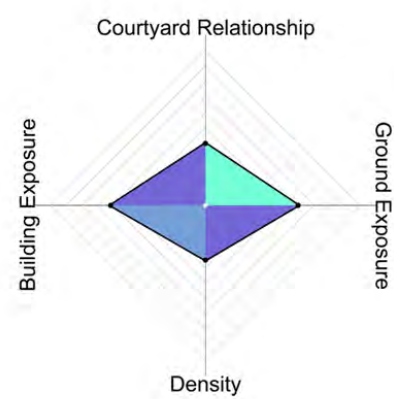
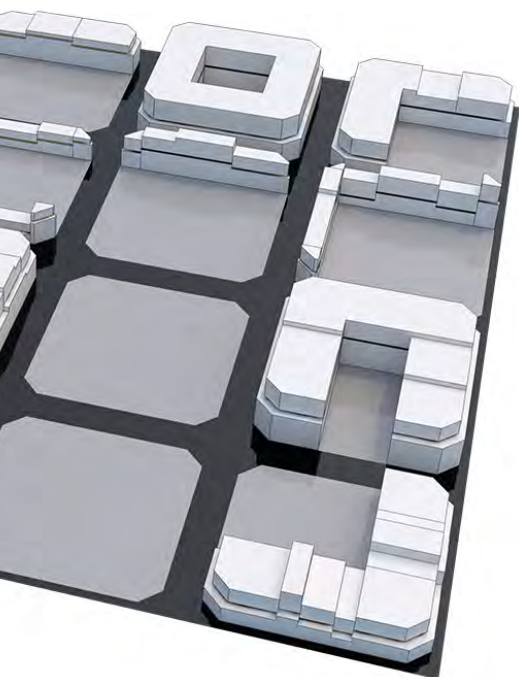
Generation 16 // Ind. 89

Courtyard Relationship
Rank: 3578 / 9900
Fitness Value: 24

Ground Exposure
Rank: 5559 / 9900
Fitness Value: 2790

Density
Rank: 3023 / 9900
Fitness Value: 17675

Building Exposure
Rank: 6111 / 9900
Fitness Value: 3739



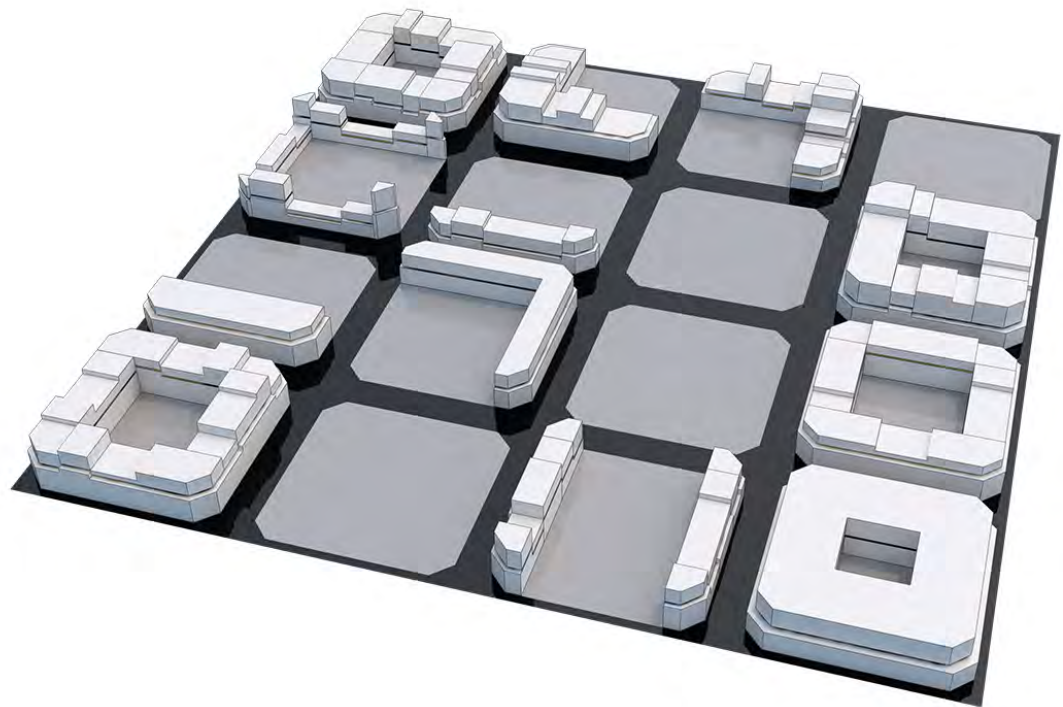
Generation 63 // Ind. 70

Courtyard Relationship
Rank: 3827 / 9900
Fitness Value: 23

Ground Exposure
Rank: 5834 / 9900
Fitness Value: 2758

Density
Rank: 3358 / 9900
Fitness Value: 16989

Building Exposure
Rank: 5972 / 9900
Fitness Value: 3788



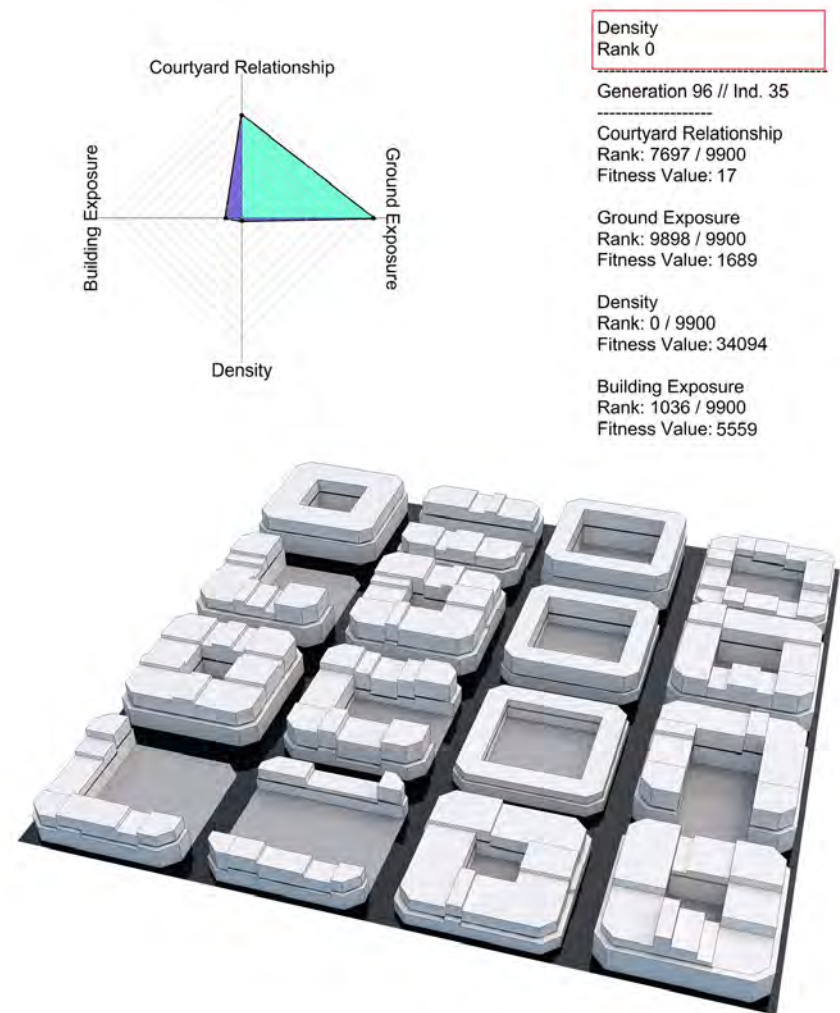
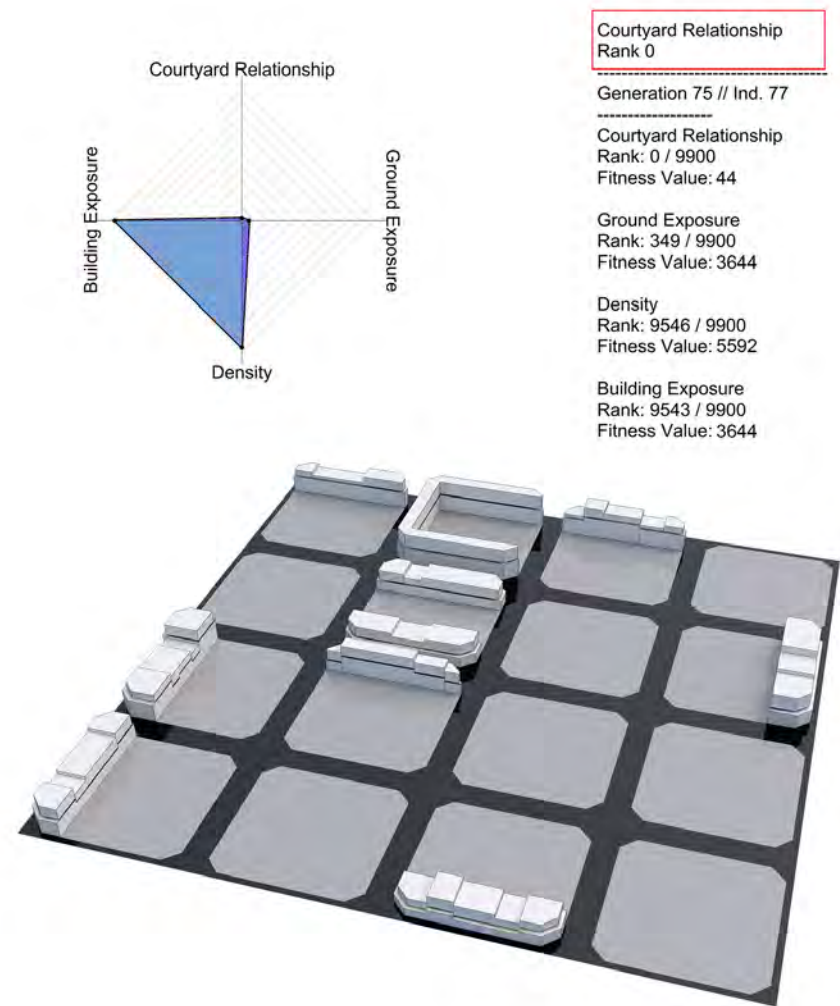
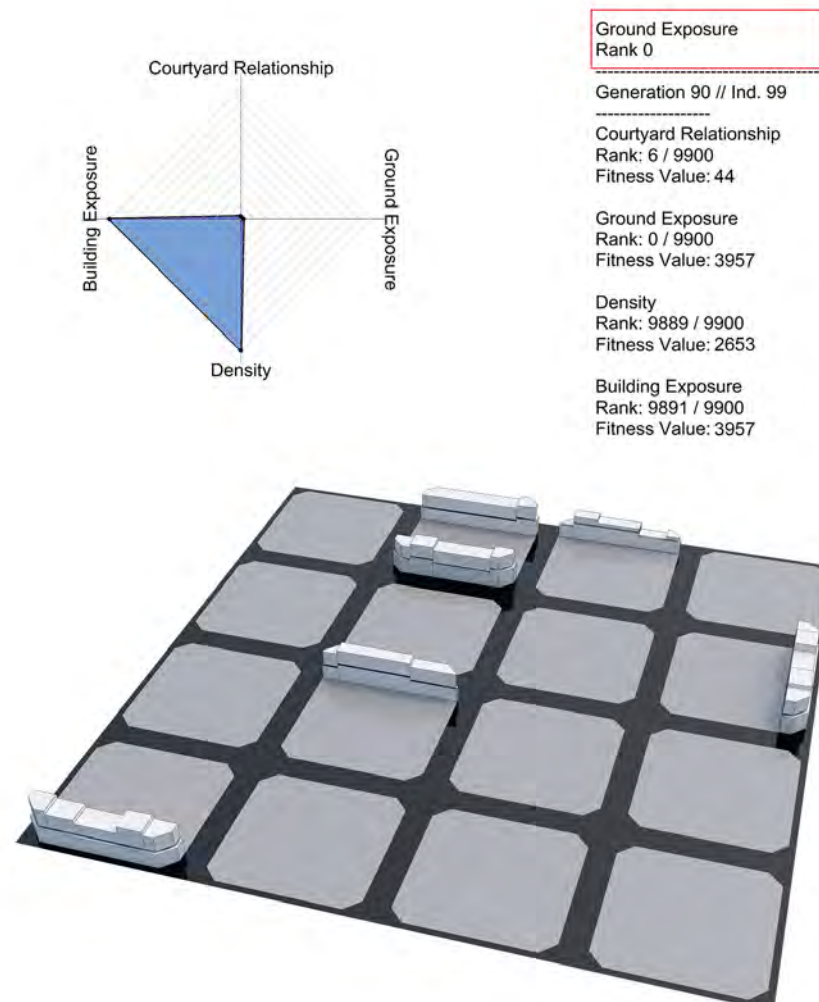
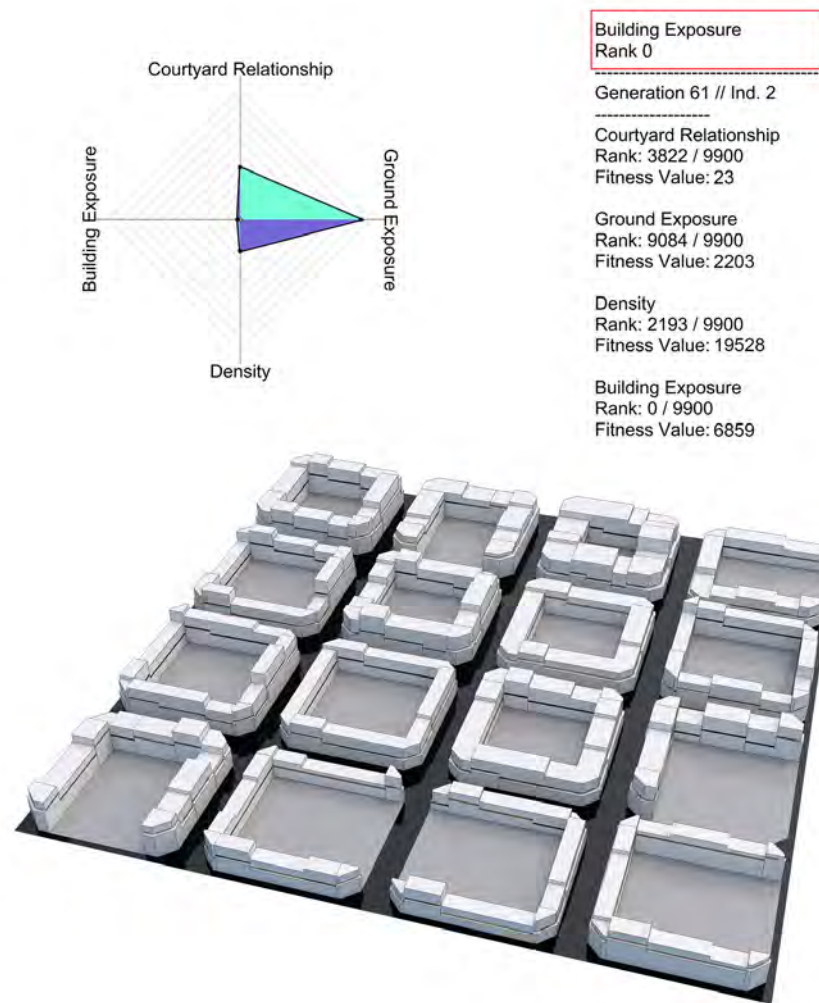


Figure 4.20.
The fittest solutions and their
relative location for each of
fitness objective.



4.3.4. Analysis

In each of the four fitness objectives driving the simulation, variation among solutions increased as the solver reached later generations (figure 4.13.). More specifically, in the *building exposure*, *connectivity* and *courtyard exposure* objectives, the variation of solutions among the population stabilised approximately midway through the simulation, at which point it fluctuated around the same value (some presented higher degrees of fluctuation over others). With regards to the mean fitness trendline for each objective, the greatest improvement was for the *connectivity* objective, with little to no improvement of the mean value in the other objectives. As discussed in chapter 3, the mean value is indicative of which *direction* the simulation is moving towards and *not* a representative of a specific solution in the population, therefore by maintaining the mean value yet increasing variance among the population, the solver seems to be evolving increased diversity of solutions through exploring a single, relatively wide hill on the fitness landscape.

The 'equally' conflicting nature of the fitness objectives set out in the reformulation of the design problem is most likely the primary cause for the increased variation in the different objectives. Due to this conflict, no single objective could converge towards a local optimum, which directed the solver to equally diverge for all objectives. A 1:1 analysis between the fitness criteria in the objective space supports this; 'complimenting' objectives generate smaller pareto fronts comprised from solutions with less variation, while 'conflicting' objectives generate larger pareto fronts comprised from solutions with greater variation. Moreover, an analysis of the objective space for the entire population presents a relatively equal distribution of solutions for the four fitness criteria (figure 4.14.).

The parallel coordinate plot was utilised to select six individuals from the 10,000 solutions generated by the simulation using two different selection criteria. The first sorted the solutions based on their mean fitness rank, in which the fitness rank of each solution took precedence over the fitness value itself. This allowed for a 1:1 comparison between the different fitness objectives of each solution. The second selection method sorted the solutions according to the relative difference between each solution's fitness values, in an attempt to locate a solution that is equally fit for the different fitness objectives.

The solutions sorted for mean fitness presented an interesting relationship between the fitness objectives. The *density* and *courtyard relationship* objectives were able to increase in fitness alongside what was originally formulated as a conflicting criterion; the *courtyard relationship* objective. Moreover, although it is expected for the selected solutions to present some phenotypic similarities; which is observed in the first two solutions, there is also a degree of variation present that is visible in the third solution (figure 4.18).

In contrast, sorting the population according to the minimal relative difference between the fitness values of each solution provides three very similar results with respect to the numerical data associated with each solution, and the location of the three solutions in the objective space.

However, the phenotypic variation between the three solutions is considerable, highlighting the fact that solutions with similar fitness values may exhibit diverse morphological characteristics. This emphasises the necessity to analyse all solutions in the population and not make the incorrect assumption that a select few can represent the whole (figure 4.19).

Finally, through the use of the diamond fitness charts, the fittest solution for each objective was also located and extracted from the population. As expected, none of the fittest solutions were located in the final generation of the simulation. The fittest solutions for *density* and *ground solar exposure* were located in the later stages of the simulation (generation 96 and generation 90 respectively), while the fittest solutions for the *courtyard relationship* and *building solar exposure* emerged in the 75th and 61st generations (respectively) (figure 4.20.).

4.3.5. Conclusions

Increasing the population size highlights the challenge of ensuring the simulation efficiently navigates the fitness landscape to maintain variation, while simultaneously moving towards global optima so as to increase the fitness of the solutions from generation to generation. Where simulations with smaller population sizes face the challenge of avoiding premature convergence towards local optima, larger population sizes are challenged with getting ‘stuck’ in optima that maintain variation but lack an improvement in fitness. One approach to encourage the solver in exploring alternative hills within the fitness landscape in order to increase fitness would be to re-run the experiment with larger mutation rates (or a smaller archive size); however by doing so, the user significantly risks the simulation favouring exploration over exploitation. Therefore, changes in the algorithm’s parameters must be coupled with the formulation of the design problem, as the former’s impact on the simulation’s navigation of the fitness landscape requires a clear expression of the latter. This highlights the significance of conducting a detailed comparative analysis of all phenotypes in the population and the numerical data associated with each solution ([Animation 2](#)).

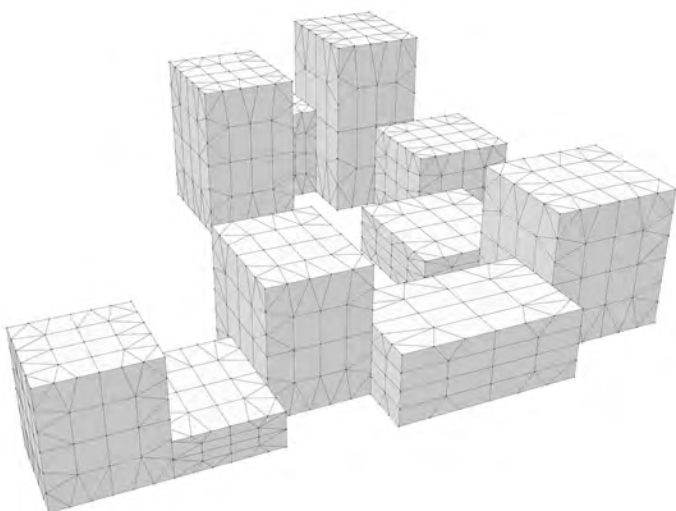
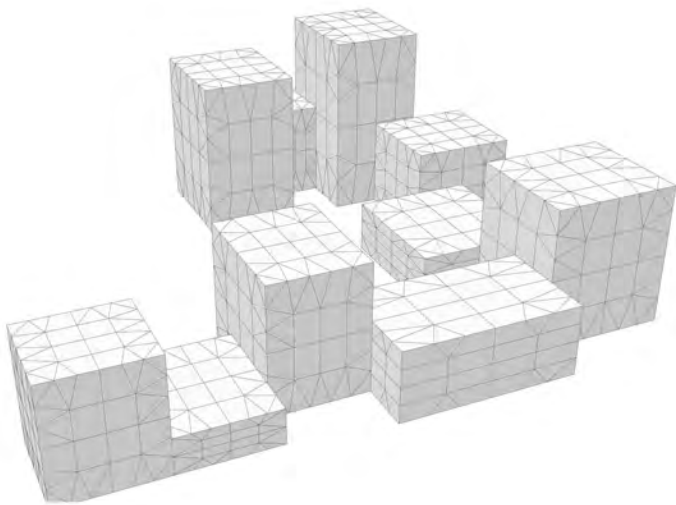
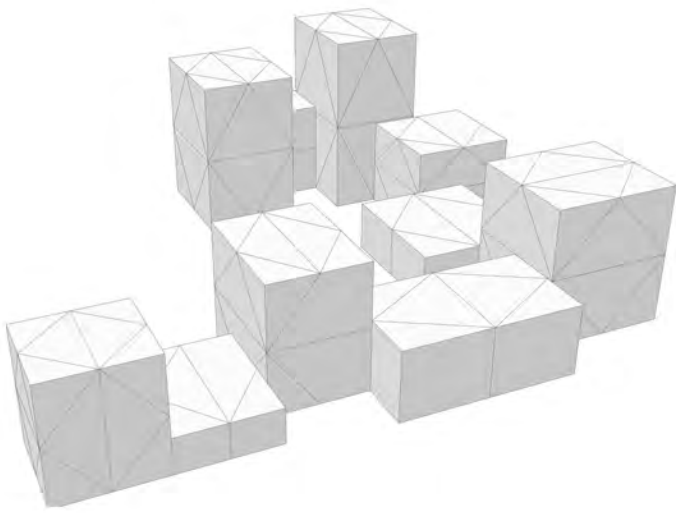
More importantly, an increased population size will always be associated with longer simulation runtimes and a higher computational load. Therefore, it is critical to address simulation runtimes and take the necessary measures to reduce them without sacrificing the complexity of the design problem. One such approach is to revisit the geometrical construction of the phenotype within the design problem. The runtime of the simulation is defined by the time required for the solver to evaluate each solution in the population. To evaluate a solution, the solver must first construct the solution in grasshopper (in order to extract the solution’s fitness values). Thus, the method by which the geometrical representation of each solution is constructed is critical to ensuring an efficient runtime. To do so, each solution’s geometry must be constructed through the minimal amount of mesh faces required. More importantly, the subdivision of the mesh faces for each geometry is equally important as this defined the precision of the solar analysis conducted on the geometry.

To conduct the solar analysis, each point on the geometry's surface (defined by the vertices of the mesh faces) is analysed with respect to a given vector. If the point can 'see' the vector, it is given a value of '1', and if it cannot, it is given a value of '0'. Therefore, to maximise solar gain on the building surface, the simulation will aim to maximise the number of '1s' for each solution. Consequently, the more points on the geometry's surface for analysis, the more detailed the solar calculation. However, increasing the geometry's subdivision (to generate more points for the solar analysis) negatively impacts the solution runtime within the simulation. When subdividing the geometry through conventional 'mesh subdivision' tools, this creates mesh faces that are relative in size to the original geometry, in which case smaller geometries have a greater impact on the solar fitness of the solution (due to them having more points for analysis), which heavily skews the results of the solar analysis. To address this, many users increase the subdivision size exponentially in the hope that by doing so, there are sufficient points on all the geometry for analysis that the difference between divisions becomes obsolete. Not only is this not proven to work, it increases the solution run time dramatically due to the high number of points being analysed.

To address this, subdividing through mesh faces must be replaced by a method that distributes equally spaced points on the geometries surface, regardless of the size of the initial geometry. Through developing this approach, the efficiency of the simulation's run time is significantly improved as it was no longer necessary to use the solar analysis tools that required a mesh (which were computationally heavy), instead utilising simpler solar tools that created the same result at a much quicker rate (figure 4.21.).

Due to the method developed above, the evaluation time per solution in experiment 2 was brought down to only 1.8 seconds, allowing for the simulation to evolve 100 generations of 100 solutions each (a total of 10,000 solutions) in only 5 hours. Minimising the evaluation time for each solution played a pivotal role in ensuring the solver was able to run and complete the simulation without crashing.

Default Mesh



Reconstructed Mesh

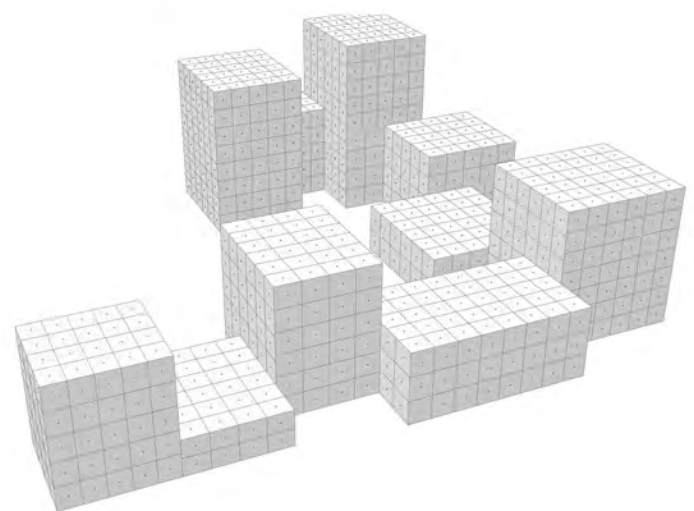
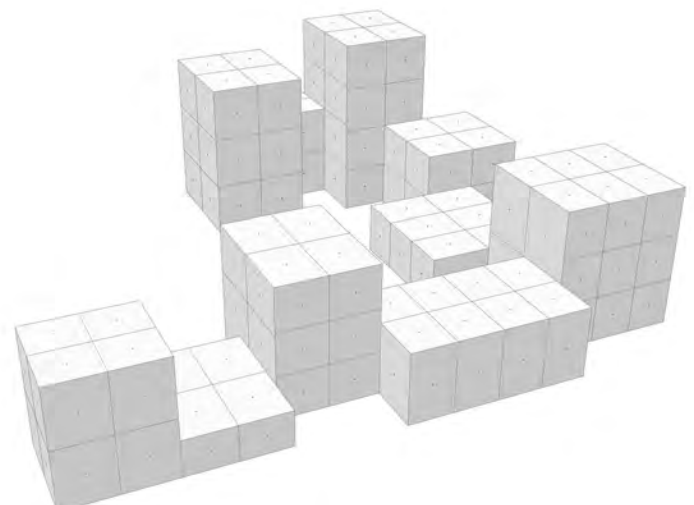
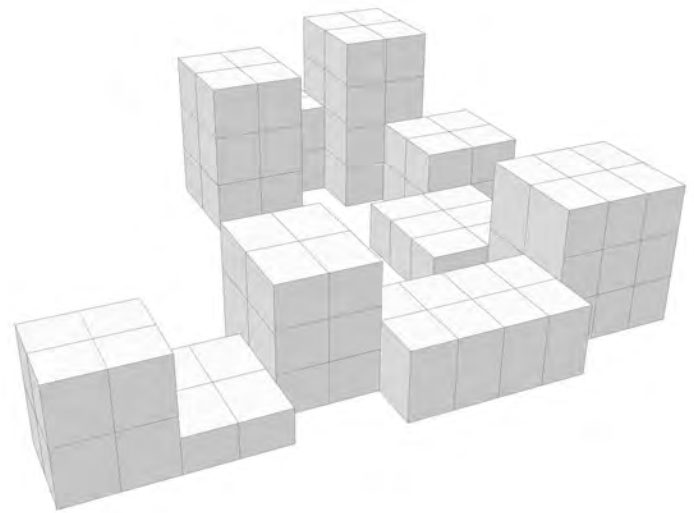


Figure 4.21.
Mesh subdivision of Geometry:
Comparison between the
default mesh subdivision of
the geometry (left) and the
developed method for mesh
subdivision (right).

4.4. Discussions

The successful application of evolutionary principles and the regulatory mechanisms associated with generating morphological variation is heavily contingent on an efficient formulation of the design problem. Running a simulation that generates copious solutions dictates the necessity for the analysis of the numerical data associated with each solution rather than the morphological evaluation of each solution's phenotypic representation. It is only through this approach that it is possible to accurately evaluate all of the generated solutions and make an informed decision for which solutions are best fitted to respond to the design problem being addressed.

Maintaining phenotypic variation in the application of evolutionary problem-solving models is a vital task in optimisation algorithms, this is more so in design, and in specific within the urban context. Variation is key to addressing complex design problems comprised from multiple conflicting objectives, therefore its preservation throughout the evolutionary solver is critical for a successful simulation and the avoidance of premature convergence. Key to this is utilising the numerical data generated by the simulation as a generative tool (rather than only an analytic one) to inform and help reformulate the design problem for maximum efficiency.

An efficient implementation of an evolutionary model within a CAD-based environment is facilitated through a practical understanding of the underlying algorithms that drive the solver, and a clear explanation of the evolutionary principles implemented within the algorithm. To achieve this, a clear delineation between single objective optimisation and multiple objective optimisation is critical to understand how the latter is a progression from the former. The result of which is a shift in mind-set from thinking about a solution to a design problem as a single entity, to one that is comprised from multiple variations, each adapting in response to a different objective within the same problem. This population-based approach presents itself as an incredibly powerful tool that is able to simultaneously address multiple conflicting objectives within the same simulation.

Equally important to the above is the computational load of running an evolutionary solver, and the different methods associated with reducing the simulation runtime to the minimum possible timeframe *without* sacrificing the simulation's performance. The significance of this is more profound when tackling very complex design problems that require large populations (large generation counts and sizes) to evolve a solution set that is both optimised and diverse. In such cases, considerable efforts must be invested in revising the method by which the phenotype is geometrically constructed in order to maximise the efficiency of its analysis by the solver.

In the experiments presented within this chapter, the design problem was formulated through a clear delineation and regulation between the genes that construct the phenotype, the body parts that comprise the phenotype, and the fitness objectives that drive the evolutionary simulation. This was applied in three experiments that differed in scale and scope, where experiment 1

demonstrated its application through the comparative analysis of a single objective problem and a multi-objective problem, experiment 2 increased the population size and demonstrated the impact of the statistical analysis of the numerical results associated with each solution on the formulation of the design problem and the selection methods that are external to the algorithmic run.

The following chapter learns from the methods developed so far and applies them in generating morphological variation of urban blocks and superblocks within two contrasting urban tissues. The experiments presented in chapter 5 evolve a population that responds to the environmental stresses of the specific context of each location and expands on the methods by which the analytic tools developed in chapter 3 are used to further advance and drive the evolutionary simulation.

Design Experiments Part II

5.1. Introduction

The following chapter builds on the methods developed thus far into generating morphological urban variation for two very different urban tissues; Norilsk (experiment 3), an 80-year-old city located in the Siberian arctic, and Fes el Bali (experiment 4), a 1200-year-old city located in the north of Africa. In addition to increasing the population size and computational load for both experiments, the complexity of the design problem is also increased in response to a larger superblock. More importantly, the significance of how the phenotype is constructed, and the impact of this on the regulation of genes, body parts and fitness objectives, is further examined. A thorough statistical analysis of the tools and methods developed in chapter 3 is conducted on the output of each experiment in order to facilitate for the selection of a solution set from the evolved population.

Through the two cities, the contrasting geographic, climatic and historic conditions provides for a comparative analysis for the application of an evolutionary model in two extreme climates. In doing so, the environmental stresses associated with the extreme climatic (and demographic) conditions drive the complexity of the design problem, and examine the adaptability of the model to create a population of solutions that are both diverse and optimised for the extreme conditions associated with each location. Additionally, the experiments analyse the differences in the formulation of the design problem and its applicability for generating urban variation on the level of the block and superblock in the context of both a *planned* city and *evolved* city.

The chapter ends with a final experiment (experiments 5) that explores methods in which the analysis of the variance levels of each generation within the population is employed to control phenotypic variation 'live' *within* the simulation's algorithmic loop. The objective of experiment 5 is to integrate some of the analytic tools developed in chapter 3 into the evolutionary solver itself, thus significantly streamlining the process of gaining a better balance between exploration and exploitation of the fitness landscape through the evolution and dynamic analysis of each solution in the population. As with experiment 1, experiment 5 is conducted in the framework of both a single objective problem (experiment 5A) and a multi-objective problem (experiment 5B), thus providing a comprehensive analysis of the developed method that ranges in scale and complexity.

5.2. Experiment 3 - Norilsk

5.2.1. Ambition

The dissolution of the Soviet Union allowed the freedom of migration of people within Russia. As a result of the inhospitable environmental conditions of the industrial cities built throughout the soviet period in the Siberian and Far Eastern Territories, much of this migration witnessed people moving out of these cities towards the south and west of Russia in search for warmer and more 'connected' locations. However, in spite of this migration, many cities in northern and eastern Siberia continued (and still continue) to thrive – mainly resulting from the continued industrial

presence due to large resource deposits; with some cities reaching populations of over 100,000 people. However, these cities were originally designed and constructed with little attention to the local environmental conditions, in which the prominent soviet superblock – the Microrayon (or microdistrict) was the dominant morphology used throughout (Graybill and Mitchneck, 2011). This has resulted in a highly unfavourable impact on the climate, the urban landscape and the living conditions of the cities inhabitants. As the climate continues to change, the urban tissues generated through the homogenous distribution of the microrayan have become less adapted to their environment, the effects of which are detrimental for an urban landscape that is experiencing continued growth.

5.2.1.1 Environmental Parameters

More and more of the world's natural resources are in locations that are geographically isolated, and under harsh environmental conditions. Despite this, cities constructed in these locations are experiencing continued growth; this is primarily within the Siberian region, in which it has the highest number of arctic cities with a population of 100,000 or more (eg. Murmansk, Yakutsk, Norilsk). To gain a comprehensive understanding of the environmental conditions associated with the region, and within the context of the formulation of the design problem, the environmental drivers of climate, ecology, resources and population associated with the Siberian territories are summarised below.

Climate

The climate of the Siberian and Far-Eastern regions varies greatly due to the vast area of the territory. Although average June temperatures are similar within several cities throughout the region (between 12°C – 25°C), average January temperature differ significantly; while cities in the north (e.g. Yakutsk) reach January temperatures of -43°C, southern cities (e.g. Krasnoyarsk) reach temperatures of -17°C (Hill and Gaddy, 2003). The annual difference in summer and winter temperatures of northern cities intensified the speed by which the permafrost regions are retreating northwards in which the thawing of the permafrost has had adverse effects on the infrastructure of northern cities. The rising summer temperatures in the northern regions has been detrimental to the city's street and rail network (decreasing the probability of railway expansion to reach these cities), and the structural integrity of the vast majority of the building morphology constructed during the Soviet period. As the effects of climate change begin to take shape in the Siberian territories, the necessity for the urban fabric of the cities affected by the climatic conditions to reorganize and adapt to the challenges presented is paramount for the longevity of these cities.

Ecology

The ecology of the Siberian region is widely diverse due to the immense span of the territory. However, unlike the adverse effects of the diminishing permafrost has on the structural integrity of the urban fabric, the thawing of the permafrost proves to be advantageous to the flora (and to some extent the fauna) of the region. Chiavari and Pallemmaerts (2008) state that the

rising temperatures and thawing of the permafrost instigated by changes in climatic conditions “lead to the opportunity for an expansion of agriculture and forestry (provided that markets or infrastructure exist or are developed)”. The longer growing seasons instigated by rising temperatures will result in higher crop yields and introduce the possibility of new crop species within these regions (Smith, 2011). The longevity of increasingly diverse agricultural seasons strengthens the probability of ‘isolated’ cities to sustain themselves locally. This questions the potential of reintroducing the principles of the agrarian city as a model for the sustainability of the cities located in the northern territories of Siberia and the Far-East.

Resources

Hill and Gaddy (2003) argue that Siberia’s vast abundance of resources, considered to be the region’s most valuable asset, is in reality the source of Russia’s greatest weakness. The Soviet industrialization of the Siberian territory resulted in the development of cities located in remote regions with the sole purpose of exploiting the resources within the territory. Although these centrally planned cities were largely subsidized by the Soviet government, the true cost of these cities was discovered after the collapse of the Soviet Union. Cities that were originally intended to provide economic profitability to the country, have now become economic liabilities. The isolation of these cities without the subsidies of the Soviet government have emphasized the challenges of the cities face to sustain themselves and establish economic self-sufficiency. Although rich in resources (oil, gas, minerals, etc.), the complexity of developing urban tissues that are capable to exploit the natural resources of the region while simultaneously succeeding in developing a sustainable urban fabric to support the population residing within the city remains unresolved and is to be addressed in the experiments conducted.

Population

The demographics across the Siberian and Far-Eastern territories are noticeably diverse. City populations range from 1.5 million (Novosibirsk) to 0.17 million (Norilsk). However, more significant to Siberia’s future demographics is the analysis of the natural population growth rates of the different territories of Russia. The regions in Russia experiencing the highest growth rates are those located within the Siberian territories (cities considered to be economically non-viable), compared to the declining growth rates of cities located in the European part of Russia (cities considered as economically self-sufficient) (Federal state statistics, 2012). The rise in population throughout the Siberian territory necessitates the revision of the notion proposed by researchers in the field to de-populate the Siberian territories towards cities located in warmer climates that are in close proximity to European markets. Rather, development of urban tissues that address and adapt to population growth through sustainability and self-sufficiency is fundamental for the longevity of cities located in the remote regions of the Siberian and Far-Eastern territories.

5.2.1.2. The City of Norilsk

Situated 300 km north of the arctic circle and with a population exceeding 180,000 (Federal State Statistics Service, 2018), Norilsk is recorded as the world's second largest city located in the arctic. It is home to vast reserves of natural resources, the major ones being Nickel (a third of the world's reserves) Platinum (40% of the world's reserves), and substantial quantities of cobalt and copper (Ertz, 2013). Established as a relatively small industrial town in the 1930s, it experienced radical transformation and growth throughout the 20th century, transforming it into one of the most densely populated cities of the northern Siberian territories and the world (figures 5.1. and 5.2.).



While other cities in the arctic were being developed throughout the same period in northern America, their scale vastly differed than those constructed in Russia. The former were built according to free market conditions, and so their size reflected this. The latter however were built primarily through the use of forced labour (most notably through the Gulag), which allowed for their exponential growth despite their isolation and remoteness from other cities in the region (Ertz, 2013; Sharapova and Richardson, 2007; Helque, 2004; Hill and Gaddy, 2003). Moreover, Norilsk's direct association to the industrial extraction of natural resources, and the scale at which this is being conducted (primarily through the mining company *Norilsk Nickel*) has established it as the 8th most polluted city in the world, with Chernobyl ranked at number 9 (Blacksmith Institute, 2007).

Figure 5.1.
Aerial View of the Siberian City
of Norilsk (Love, 2014).

In light of this, Hill and Gaddy (2003) make the case for a complete abandonment of the Siberian and Far-Eastern cities and the forced migration of its peoples towards cities situated closer to Eastern Europe, deeming such isolated cities as ones that should never have existed in the first place. This proposal is fiercely argued by many Russian researchers and scientists (primarily in two issues of the journal *Problems of Economic Transition*, (2006, 2007)), with the overwhelming sentiment being that the culture and society of these cities has evolved during their brief history. The inhabitants of these isolated cities do not see themselves as short term occupants or transients; generations that have lived in these cities do not see themselves as 'cursed', but rather as people of the land, living in the place where their roots grow deeper as time progresses. As anyone who values the environment they live in, their intention is to better it and not abandon it (Sharapova and Richardson, 2007). Therefore, migration towards these extreme biomes must not be inhibited, but supported by adaptation to the particularities of life in these environmental conditions.



Figure 5.2.
Aerial View of the Siberian City
of Norilsk (Tropki, 2014).

5.2.1.3. The Microrayon

The urban fabric of Norilsk is comprised primarily from the microrayon (or microdistrict), a 10-storey housing block distributed repetitively throughout the urban landscape (Jull, 2014). The microrayon was the typical mega-block created and implemented by the Soviet Union to address mass housing of large populations in a block that also housed the services required by the residents. These services included schools, retail units, playgrounds, supermarkets and public service offices. Although the boundary of the microrayon was defined by vehicular street networks, the microrayon itself was considered a pedestrian only zone, with emphasis given to open space; hence the residential units were built to meet the requirement, allocating all other space as public space (Jull, 2016). Implemented across all regions of the Soviet Union, the microrayon was intended to become a symbol of efficient and equal living that addressed the rapid period of urbanisation of the region in the first half of the 20th century. However, regardless of the geographic and environmental context, microrayons were built based on standardised plans, therefore a microrayan built in either Novosibirsk or in Moscow were strikingly similar (figure 5.3.). Absent from soviet planning principles were environmental impact concerns and environmental constraints (Graybill and Mitchneck, 2011).

In Norilsk, the distribution of the microrayon was similar to other parts of the region, in which the structure was situated within a grid throughout the city. Although adjacent blocks were arranged with the aim of reducing prevailing winds and maximising solar gain, the former took precedence over the latter as the close proximity and height of the microrayons created significant overshadowing between blocks which in turn minimised solar gain both on ground level and on the building envelope (Jull, 2016). It is in this context that the design problem in the following experiment is formulated.



Figure 5.3.
Use of the Microrayon
repeated within a grid
throughout the city.

5.2.2. Experiment Setup

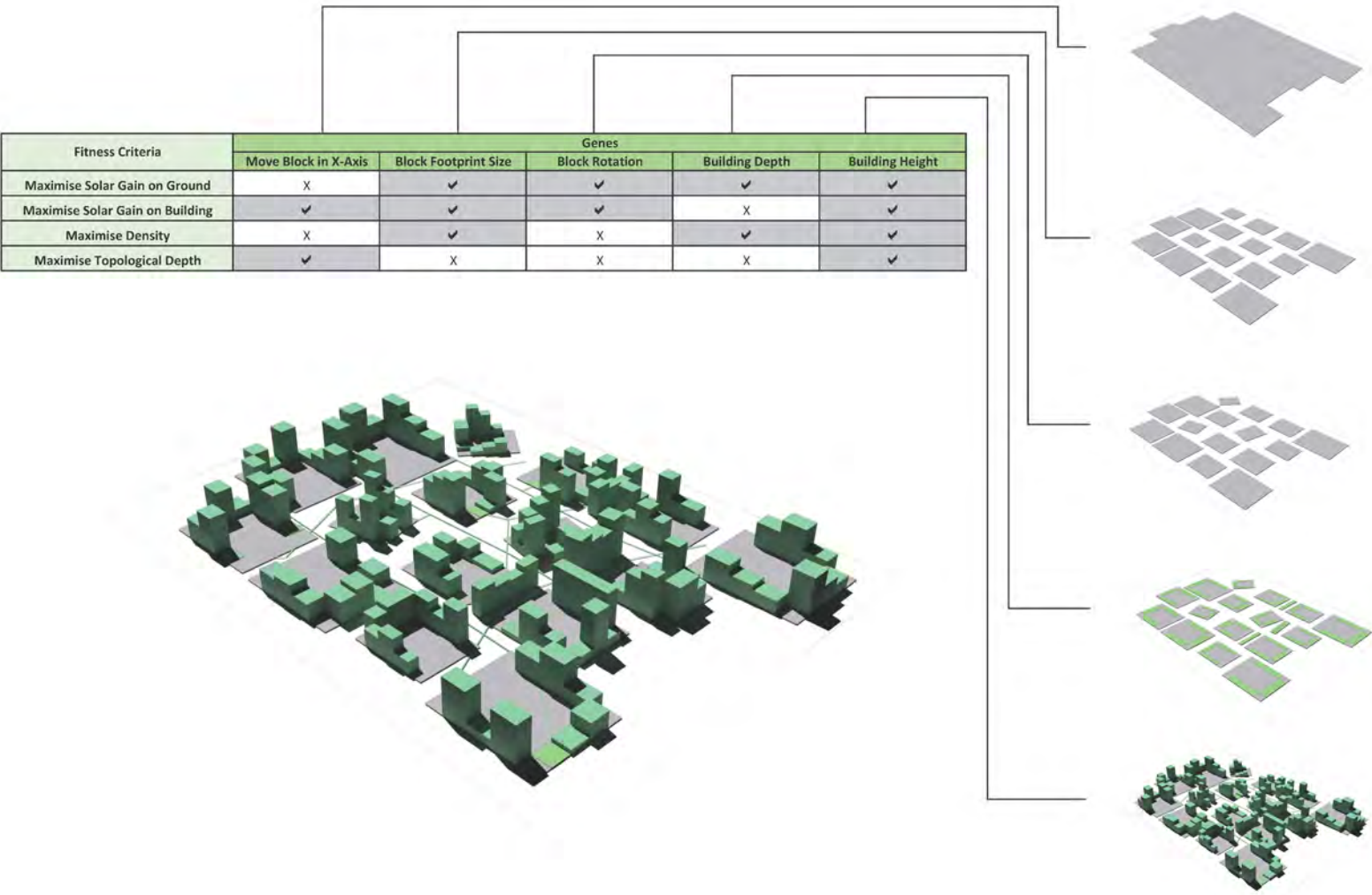
The Microrayon serves as the primary phenotype for the following experiment. Following on from the Barcelona experiments, it is concluded that the superblock is a robust primitive for an evolutionary simulation as it allows for the formulation of the design problem to incorporate relations between neighbouring blocks, thus minimising repetition of single blocks and avoiding the requirement to array a block multiple times in the X and/or Y. Moreover, the superblock provides sufficient data to establish a body plan within the phenotype and consequently the regulation of genes and fitness criteria to each body part.

The primary objective of the experiment is to achieve urban variation within the Microrayon that generates sufficient solar gain (both on ground level and on the building envelope) through a variation of the blocks' distribution and morphological composition. To achieve this, the design problem is formulated to optimise for maximising solar gain on ground level, maximising solar gain on the building envelope, maximising density and maximising the topological depth between the different blocks within the superblock (figure 5.4.).

Through maximising the topological depth within the superblock, the design problem attempts to drive the simulation towards 'breaking free' from the linear and grid like distribution of the conventional microrayon towards one that allows for a greater likelihood of the simulation evolving solutions that are able to meet the other 3 fitness objectives. Moreover, the solar analysis conducted in the simulation utilises a low sun angle extracted from the region's actual sun path to ensure the impact of overshadowing within the superblock is correctly accounted for within the simulation.

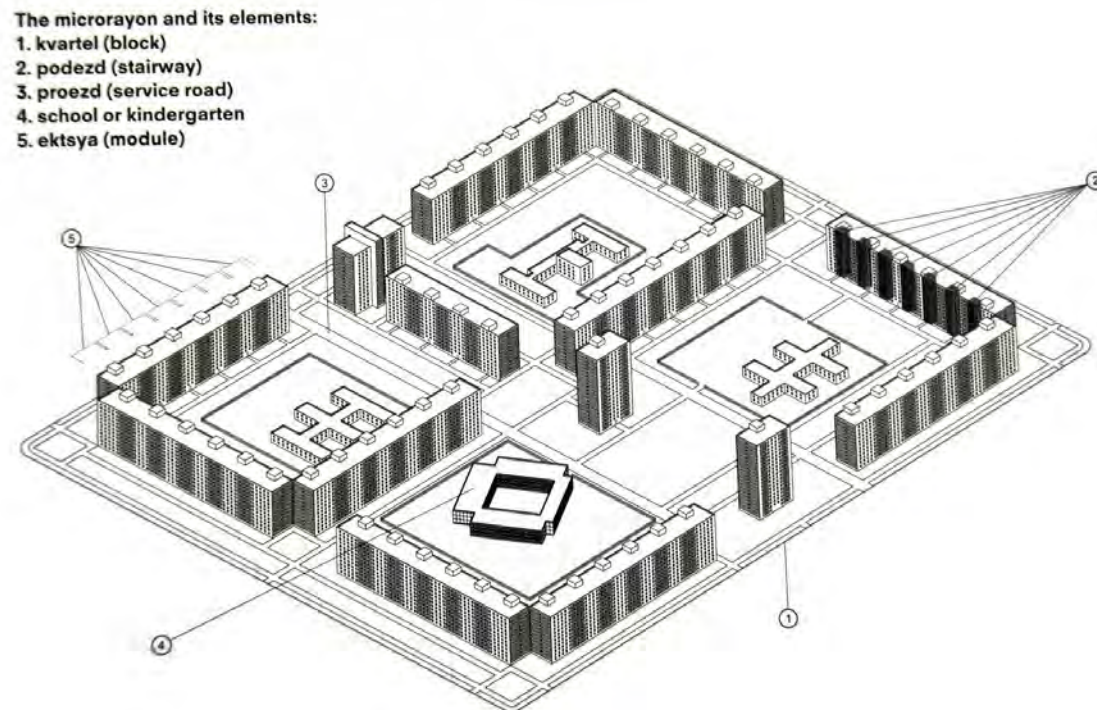
Goal	<i>Generate an urban superblock that addresses the extreme climatic conditions of Norilsk, by attempting to maximise solar gain both on building and on ground while simultaneously increasing density through allowing each block within the superblock to 'move' freely in relation to the neighbouring block.</i>
Objectives	<ul style="list-style-type: none"> • <i>High solar gain on ground and on the buildings</i> • <i>Break the linearity within the superblock</i> • <i>Account for high levels of density</i> • <i>Increase the connectivity between and through adjacent blocks</i>
Fitness Criteria	<ul style="list-style-type: none"> • <i>Maximise solar gain on ground level</i> • <i>Maximise solar gain on building envelope</i> • <i>Maximise Density</i> • <i>Maximise topological depth between blocks</i>
Phenotype	<i>4x4 superblock comprised from the Microrayon</i>
Gene Pool	<ul style="list-style-type: none"> • <i>Move blocks in X-axis</i> • <i>Change size of block footprint</i> • <i>Allow blocks to rotate</i> • <i>Change size of courtyard (building depth)</i> • <i>Change heights of each building unit within a block</i>

Figure 5.4.
Design Problem – Experiment
3: Summary of the design
problem and description of
how the fitness objectives,
gene sequences and body
parts regulate each other.



5.2.2.1. Constructing the Phenotype

The first step in formulating the design problem is clearly defining the gene sequences that define each block and the additional sequences required to define the superblock. To do this, the different components that comprise the Microrayon are highlighted into two categories, enclosing block and non-enclosing blocks. The former is comprised from multiple modules that define the block's boundary, while the latter is a series of linear towers located between the enclosing blocks (although the enclosing block has within it a secondary module, this is disregarded for the purposes of this experiment) (figure 5.5.).



To maximise the relationship and dependence of adjacent blocks to one another, the superblock is constructed as a complete unit rather than individual entities. Moreover, the microrayon is initially constructed according to its original morphology, to which variations are then incorporated within the geometry. It is important to highlight that the design problem does not add additional morphological characteristics to the microrayon, rather the experiment modifies the block's existing characteristics through revising the numeric domains to which they are bound. In doing so, three primary revisions to the block's morphology are implemented, these are clarified in the following section (figure 5.6.):

Figure 5.5.
The components that
comprise a typical microrayon
(Manifold, 2012).

Location:

The centre that defines each block is allowed to move along the X-axis. However, to avoid overlapping blocks, which will require computationally heavy geometric boolean operations (this however is addressed and solved in the following experiment), and to ensure the original modules comprising the microrayon are maintained, the movement is transcribed within each row of the superblock rather than to each block independently.

Size:

The scale of each block within the superblock is unique to itself, and not dictated by adjacent or regional conditions. This allows for significant flexibility for each block to change independent from neighbouring constraints while simultaneously responding to global conditions of the superblock.

Rotation:

To break from the orthogonal distribution of the superblock, blocks that are scaled within a specific threshold are given the freedom to rotate in response to the fitness objectives. The threshold is defined by the size and proximity of adjacent blocks to avoid overlapping between them (this is also due to minimising computational load; also addressed in the following experiment).

The heights of the individual units within each module comprising the microrayon is given the freedom to change independently. Moreover, the domain of variation in height starts at '0', thus allowing for units to be completely deleted from the superblock (this is in contrast to the experiments conducted with the Eixample superblock in which deletion was imposed on the complete side of the block rather to each unit). In doing so, the deleted units act as 'anchor points' that increase the connectivity between the main paths between the blocks to the block itself. Therefore it is assumed (in the context of the presented experiment) that deleting units within each block allows for greater connectivity throughout.

Through defining each gene's numeric domain, it allows for the calculation of the size of the experiment's search space (all possible solutions in the experiment). This signifies the impact of the size of the numeric range has on the size of the search space; a larger domain is associated with a larger search space and vice versa. Therefore, it is essential that in formulating the design problem, the domain of each gene is limited to what is *required* and does not exceed beyond that. The genes and their associated domains are listed in the following tables. The two tables compare what impact an additional decimal place in the domain of a gene has on the size of the search space. This signifies the necessity to define the gene's domain to allow the solver to generate sufficient variation while at the same time reduce the size of the search space to its minimal value.

5.2.2.2. Solver Parameters

In line with the previous experiment, the generation size was set at 100 solutions. However, in an attempt to maximise variation and allocate sufficient time for the simulation to explore the fitness landscape in search for optimal peaks, the generation count for the experiment was set at 260 generations. This was driven by multiple ‘test runs’ of the experiment that aimed to balance between the time required to evaluate each solution and the total time required to conduct the simulation (simulation and solution times are highlighted in the following section).

Moreover, due to the large generation size and count, and in line with the success of the previous experiment in generating sufficient variation throughout the simulation, the solver parameters driving the simulation were set to a Mutation Probability of 10%, Mutation Rate of 50%, Crossover Rate of 80% and an Archive Size of 50%.

Gene	Numeric Domain	Possible Solutions	Size of Search Space
Movement in X-axis	$-50.00 < x < 50.00$	100,001	4.93x10 ³²⁵
Uniform scale in X and Y	$0.50 < x < 1.00$	51	
Rotation	$0.00 < x < 90.00$	9001	
Scale of Module Depth	$0.70 < x < 1.00$	21	
Height per unit (no. of levels)	$0 < x < 10$	11	

Gene	Numeric Domain	Possible Solutions	Size of Search Space
Movement in X-axis	$-50 < x < 50$	101	6.10x10 ²⁸⁵
Uniform scale in X and Y	$0.50 < x < 1.00$	51	
Rotation	$0 < x < 90$	91	
Scale of Module Depth	$0.70 < x < 1.00$	21	
Height per unit (no. of levels)	$0 < x < 10$	11	

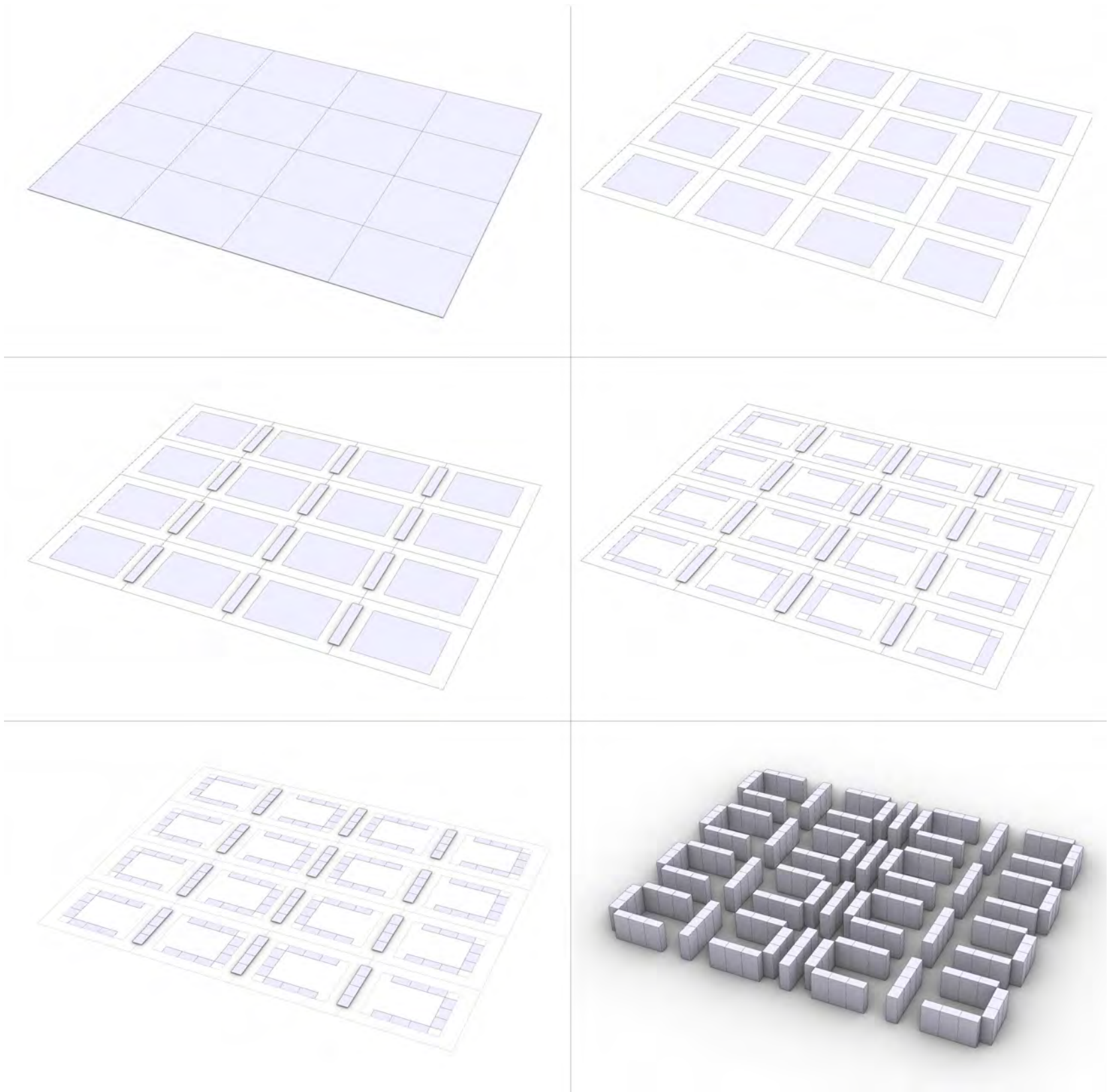


Figure 5.6.
The construction of the
microrayon in the design
problem.

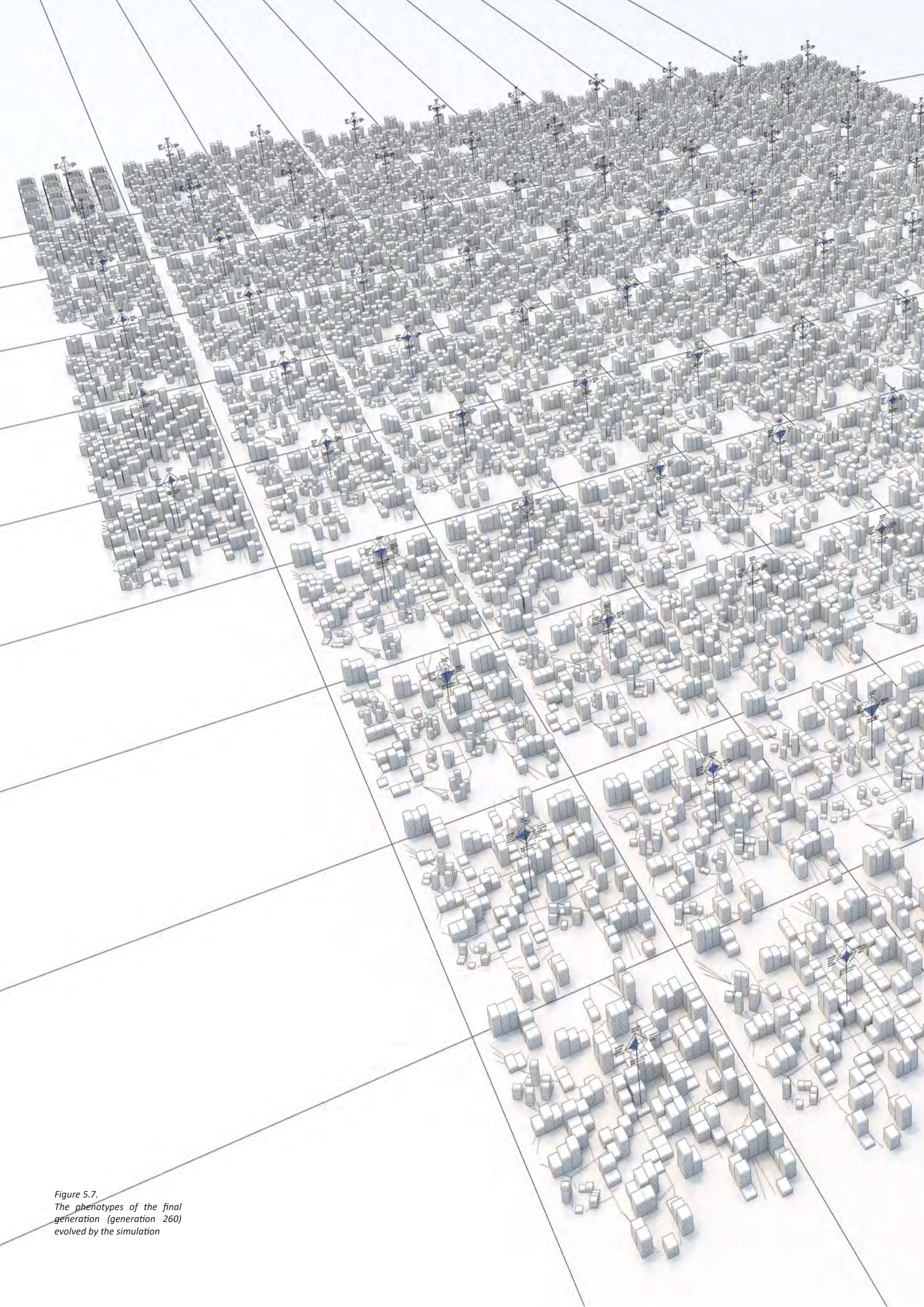
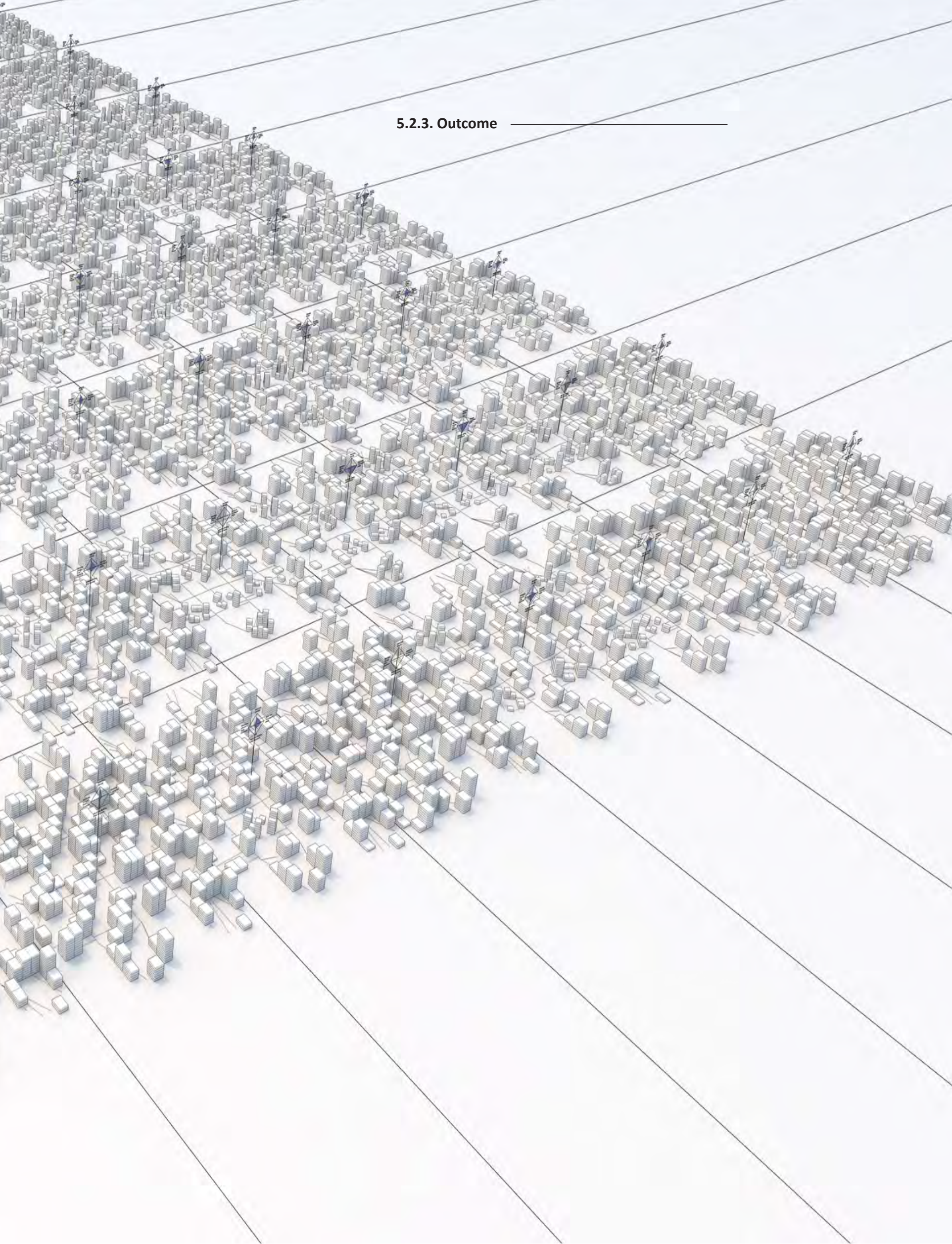


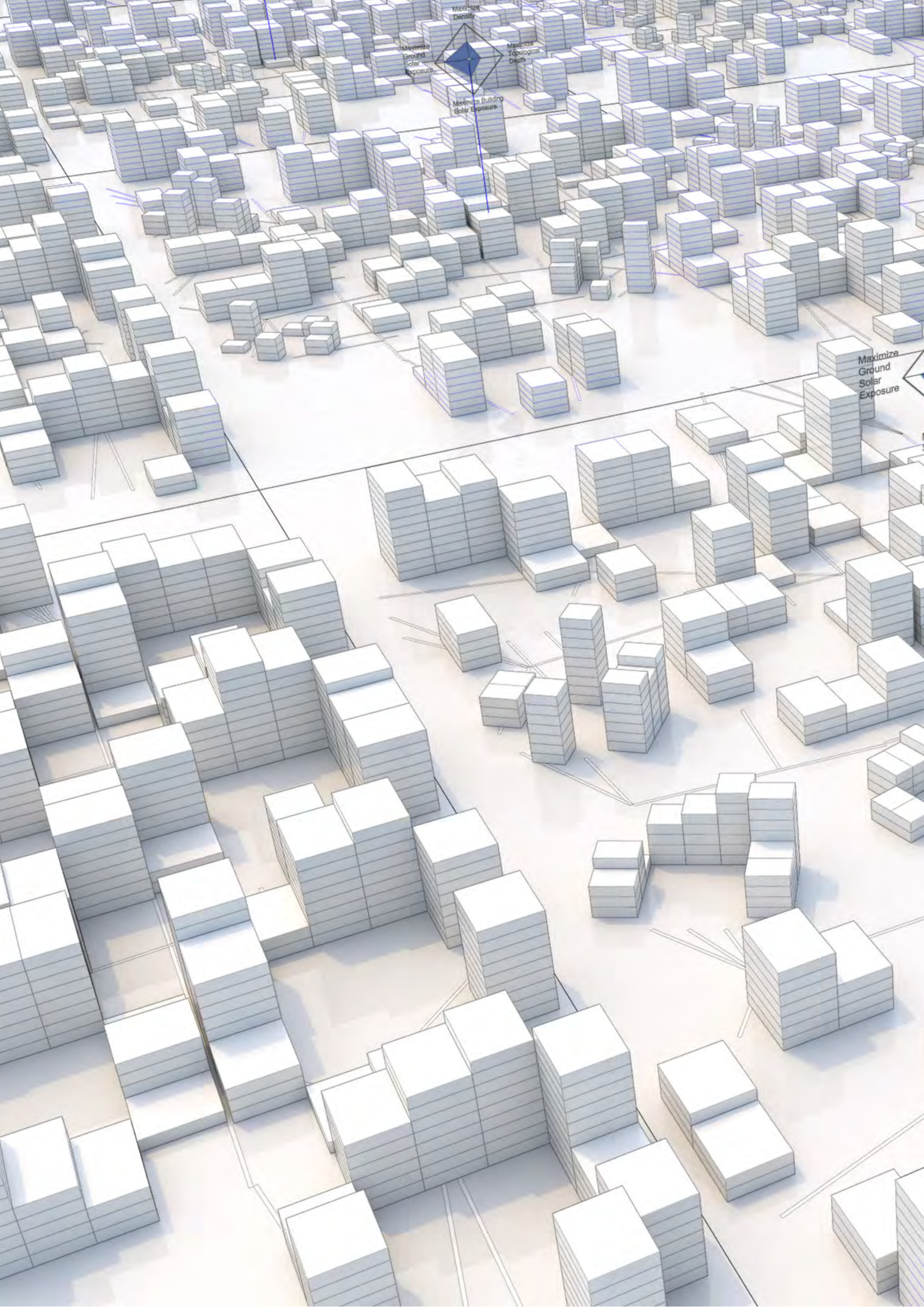
Figure 5.7.
The phenotypes of the final
generation (generation 260)
evolved by the simulation

5.2.3. Outcome









Maximize Density

Maximize Building Solar Exposure

Maximize Ground Solar Exposure



Maximize Density

Maximize Density

Maximize Ground Solar Exposure

Maximize Topological Depth

Maximize Building Solar Exposure

Maximize Topological Depth

Maximize Building Solar Exposure

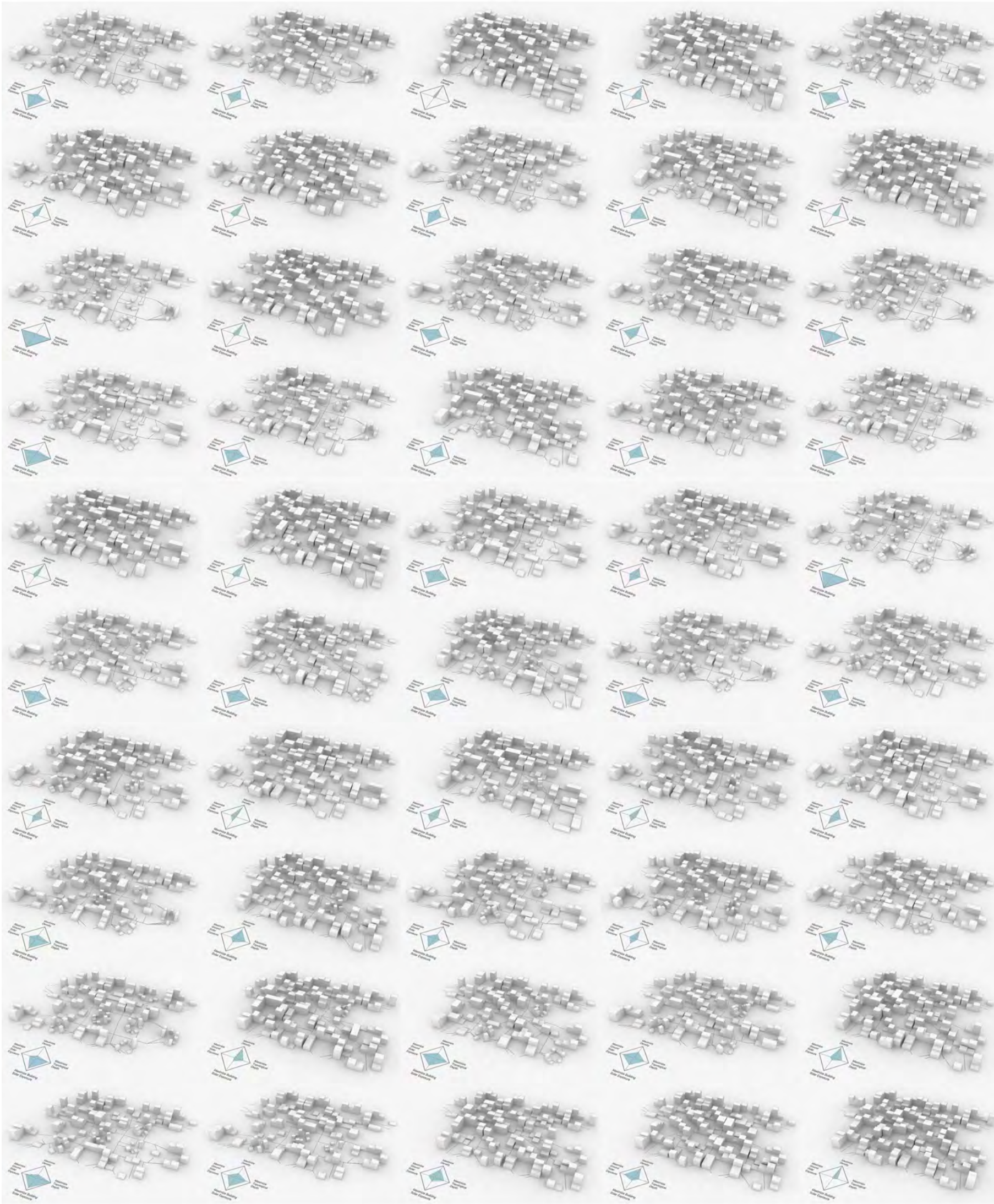
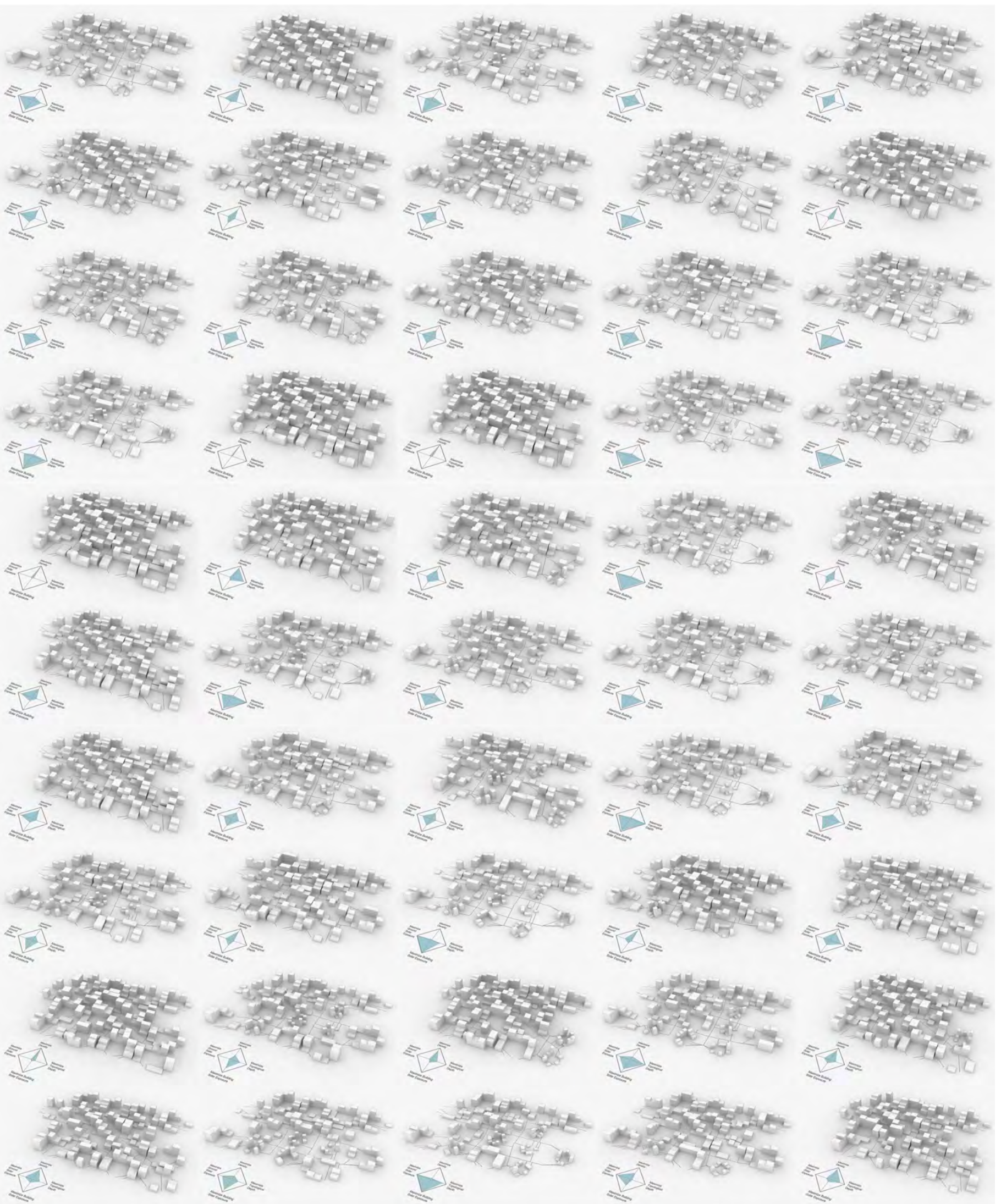


Figure 5.8.
Analysis of each solution in
the final generation through
a comparison between the
phenotype and the diamond
fitness chart.



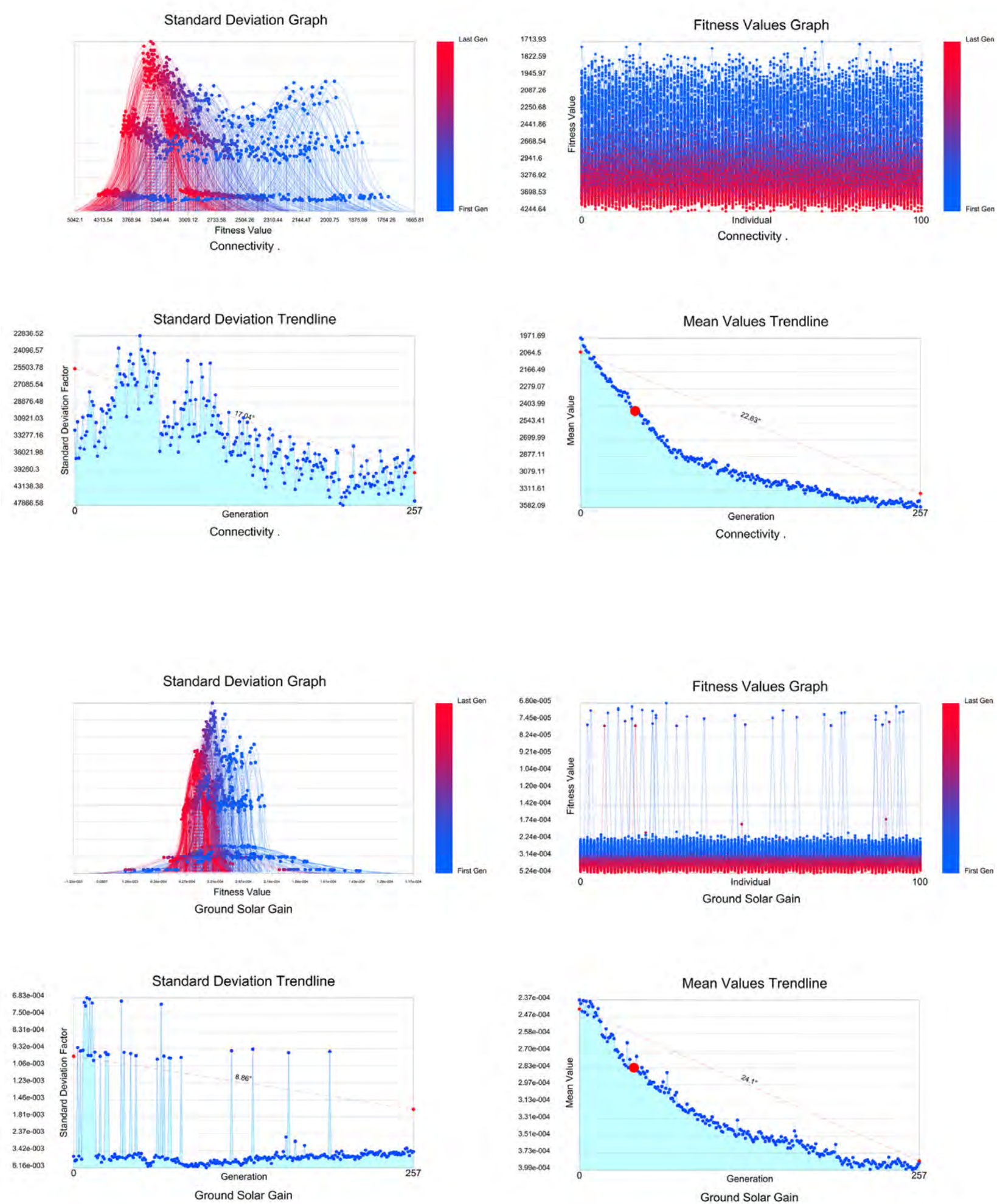
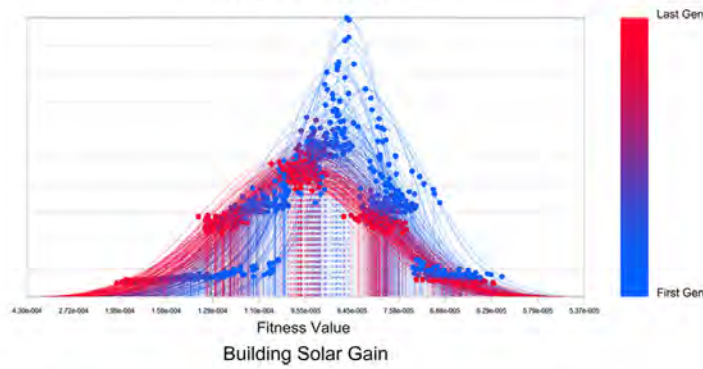
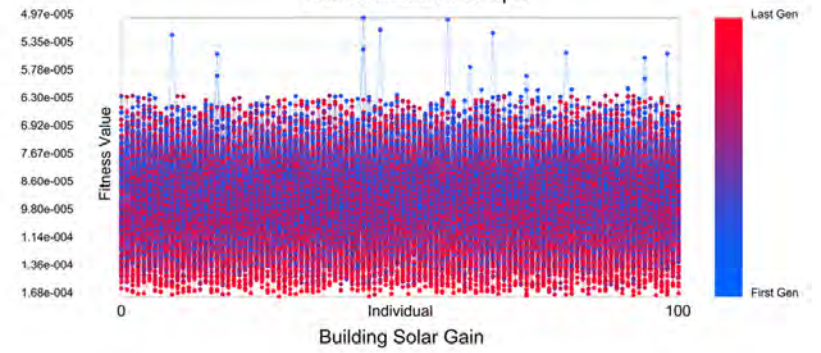


Figure 5.9.
Statistical Analysis of the
Simulations Output

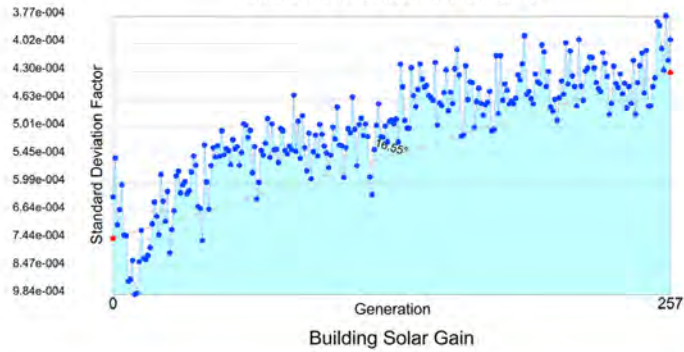
Standard Deviation Graph



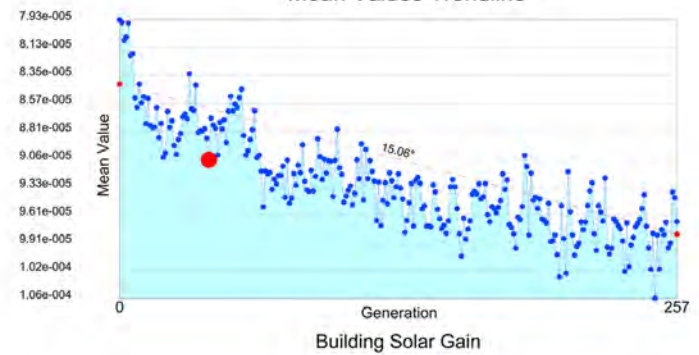
Fitness Values Graph



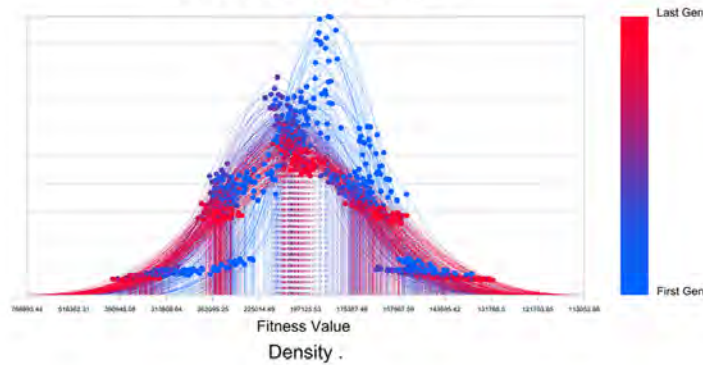
Standard Deviation Trendline



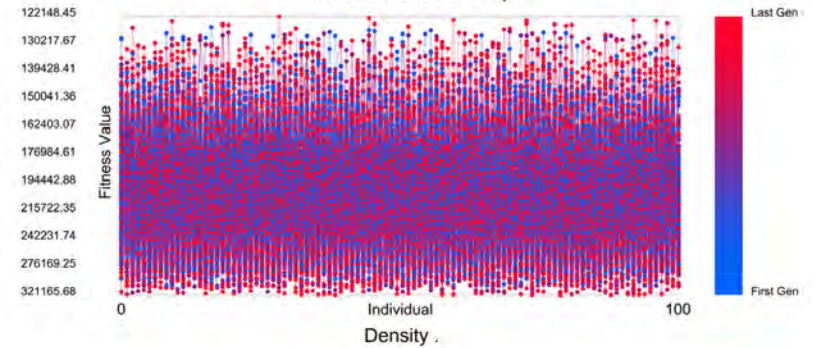
Mean Values Trendline



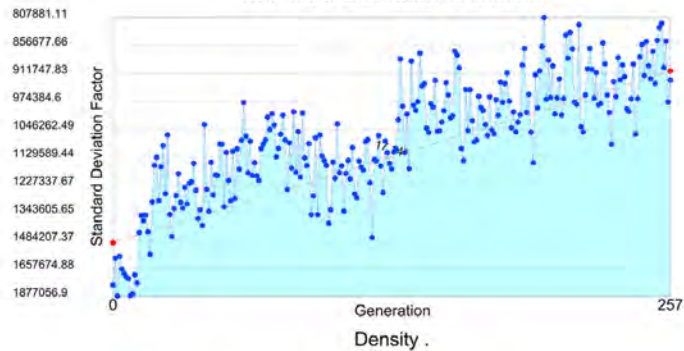
Standard Deviation Graph



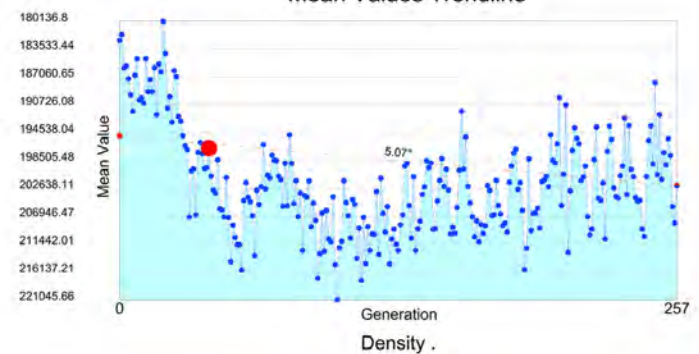
Fitness Values Graph



Standard Deviation Trendline



Mean Values Trendline



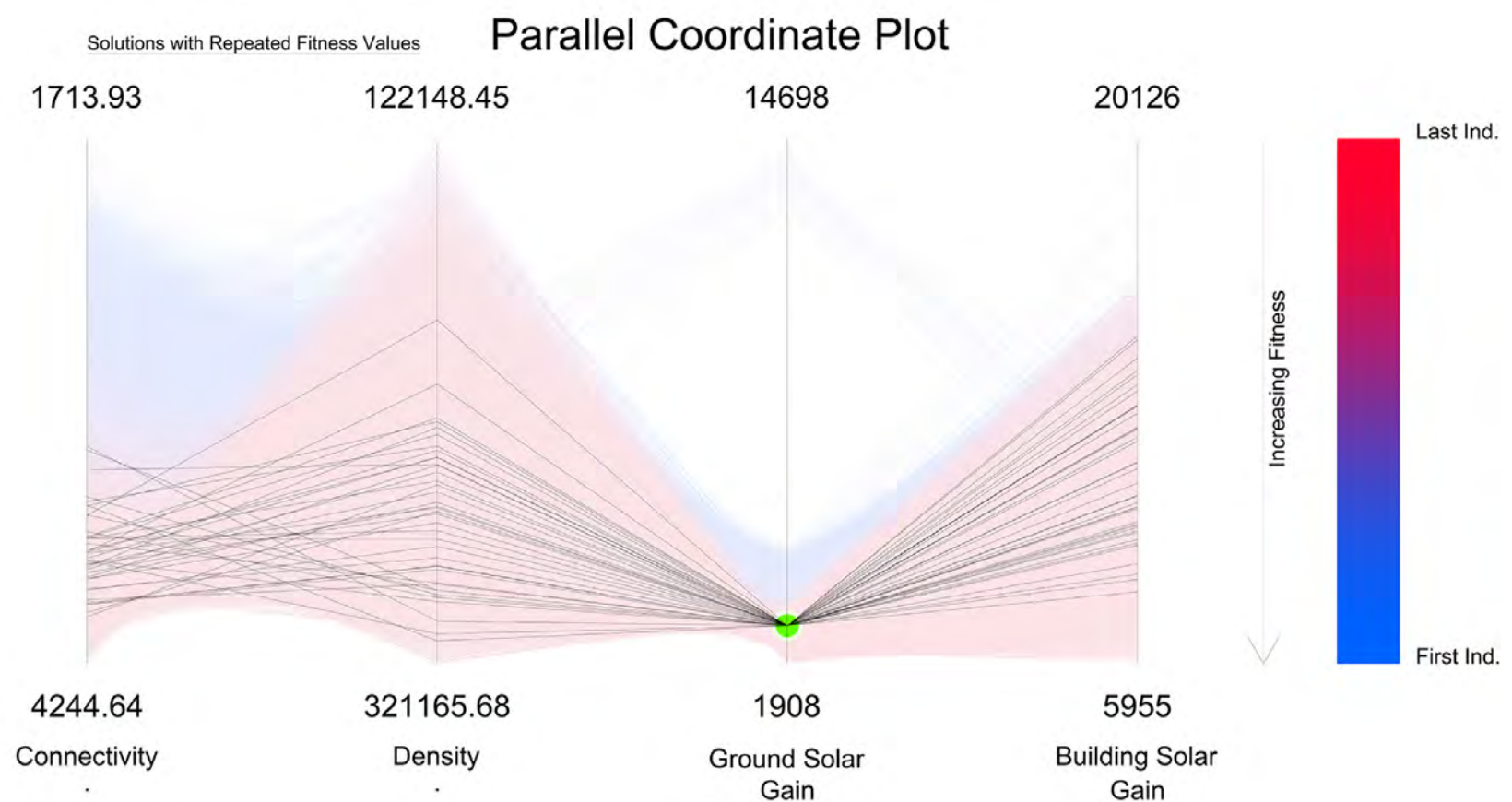
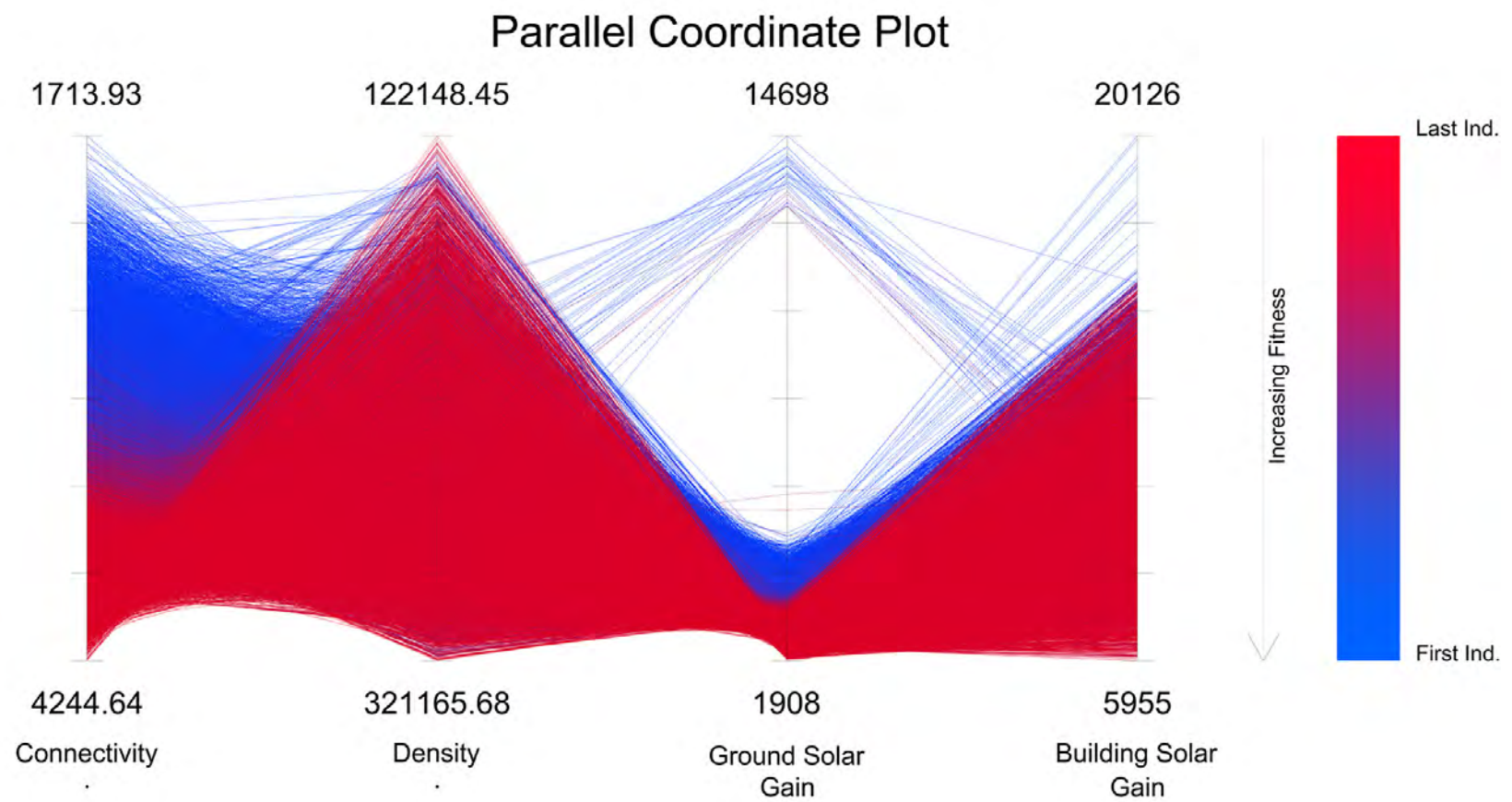
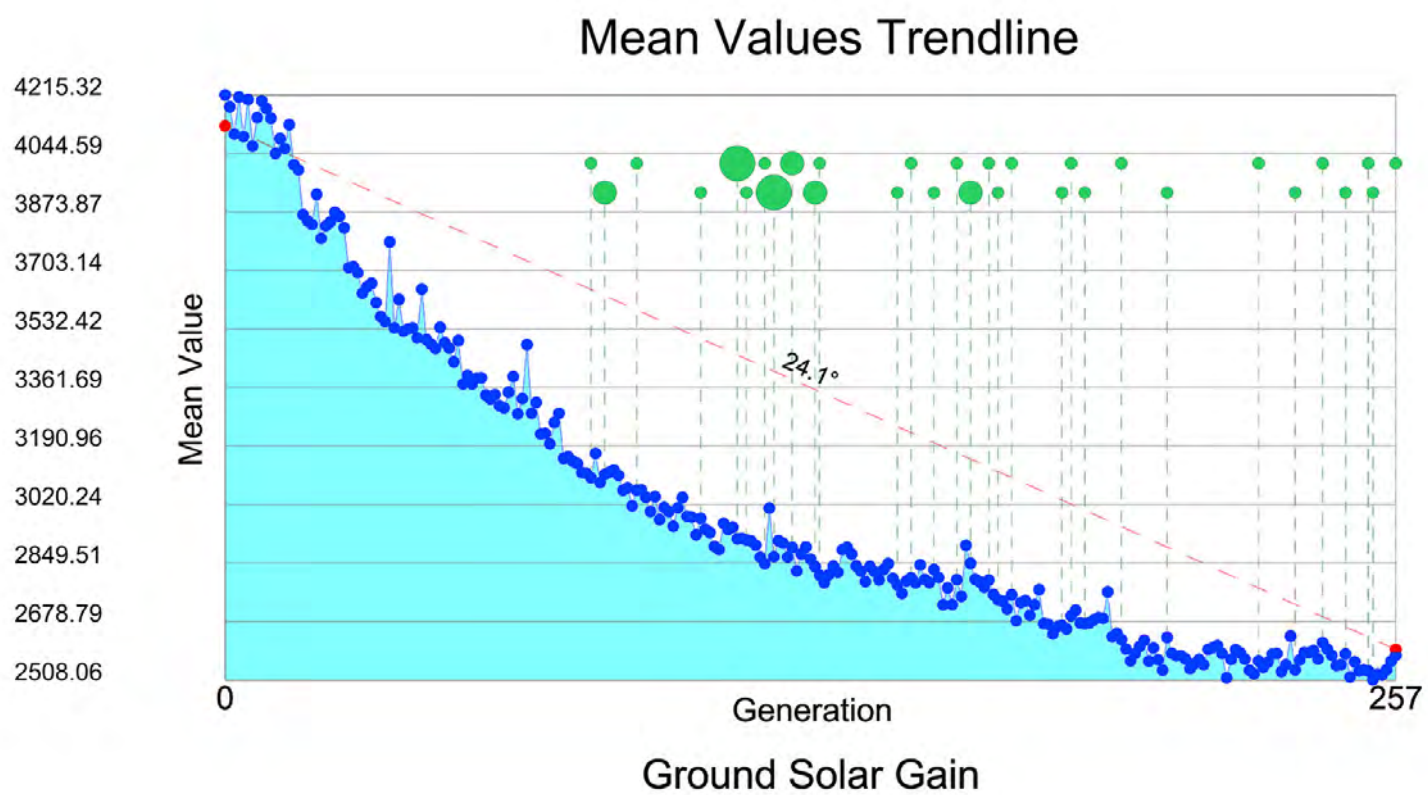
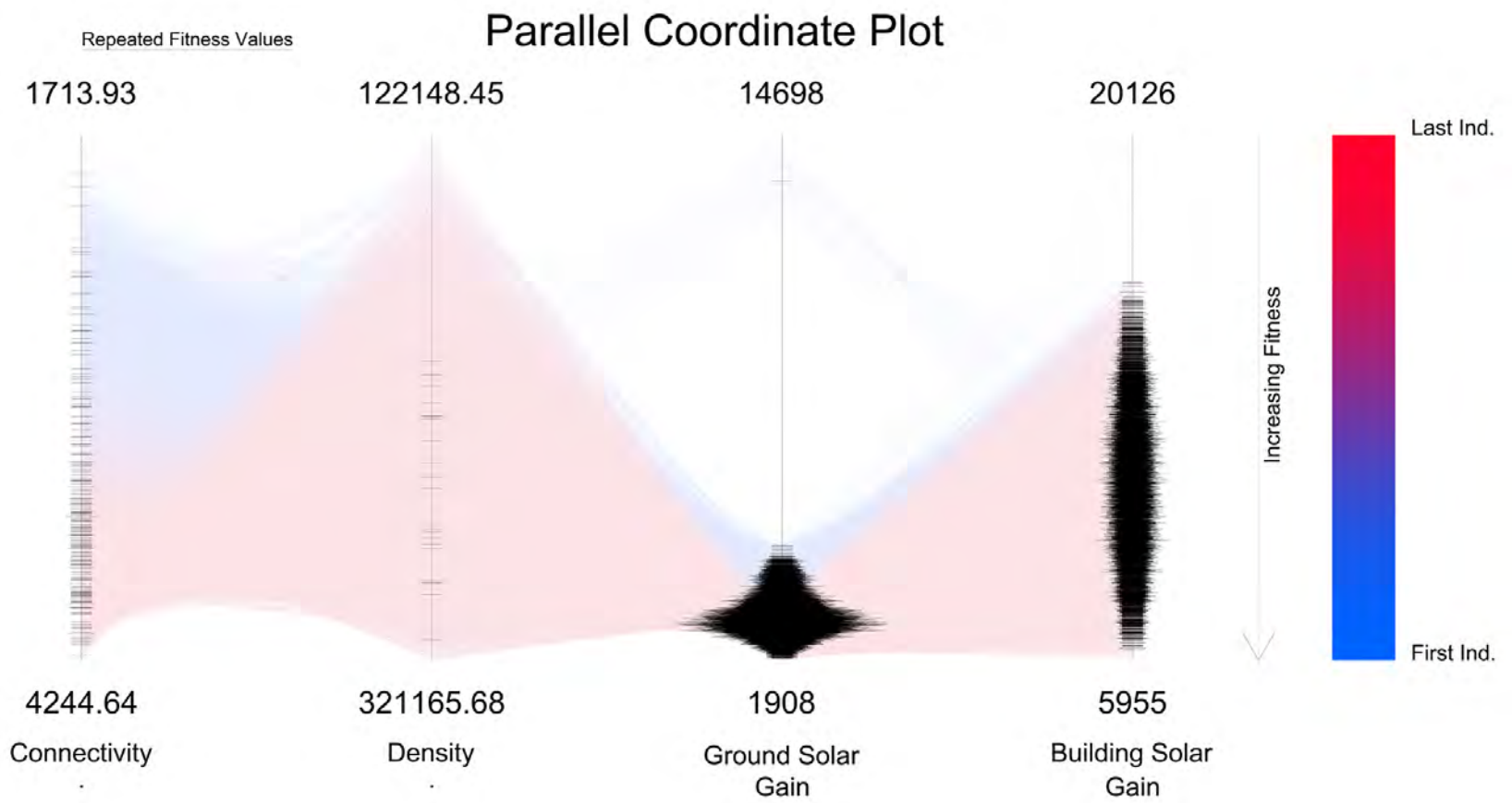


Figure 5.10.
Analysis of the simulation's
output through the parallel
coordinate plot and the
selection of the solutions
with the most repeated
fitness values. The location
of these solutions in the
different generations is also
represented.



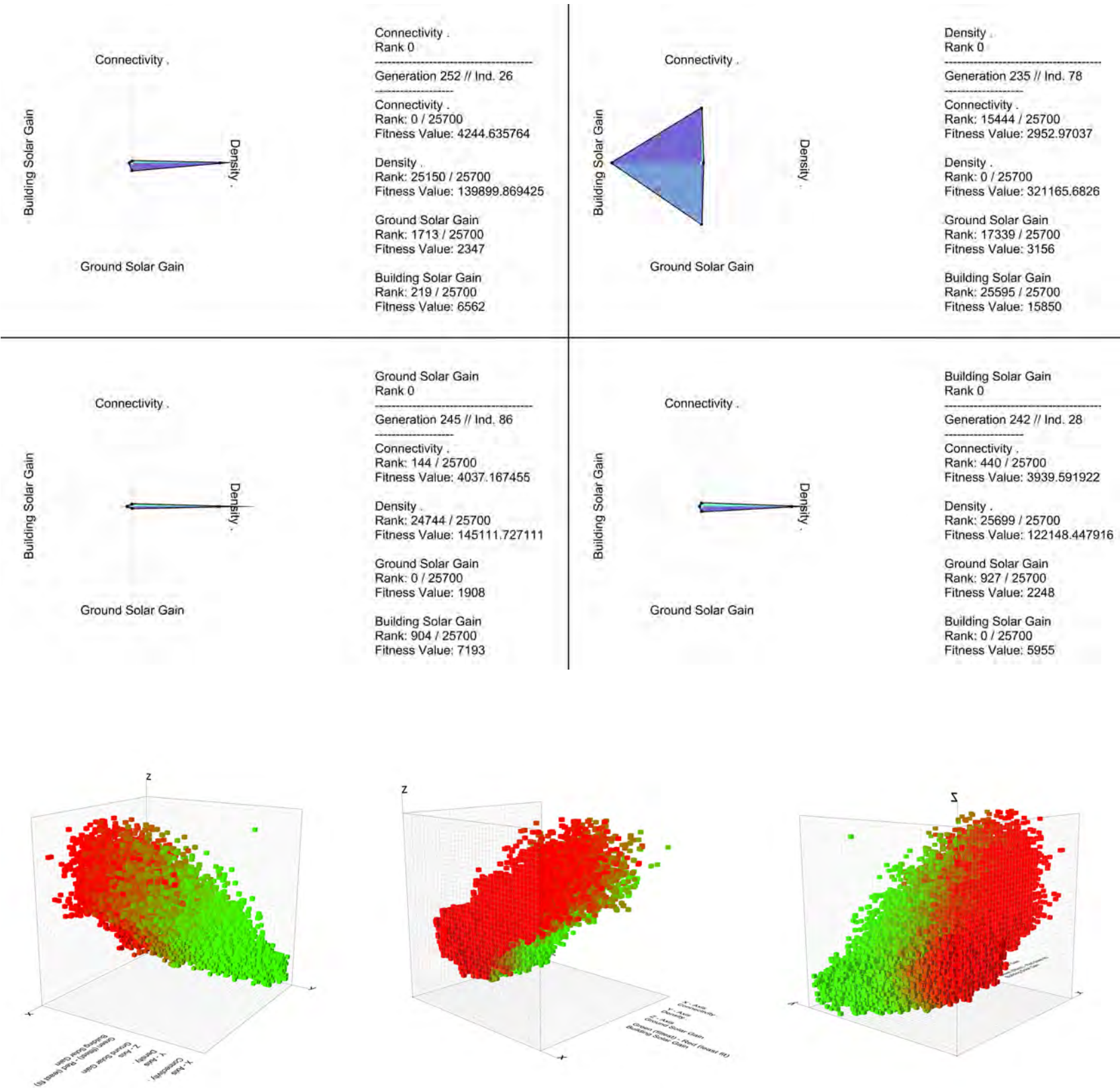


Figure 5.11.
The diamond fitness chart for
the fittest solutions for each
fitness objective.

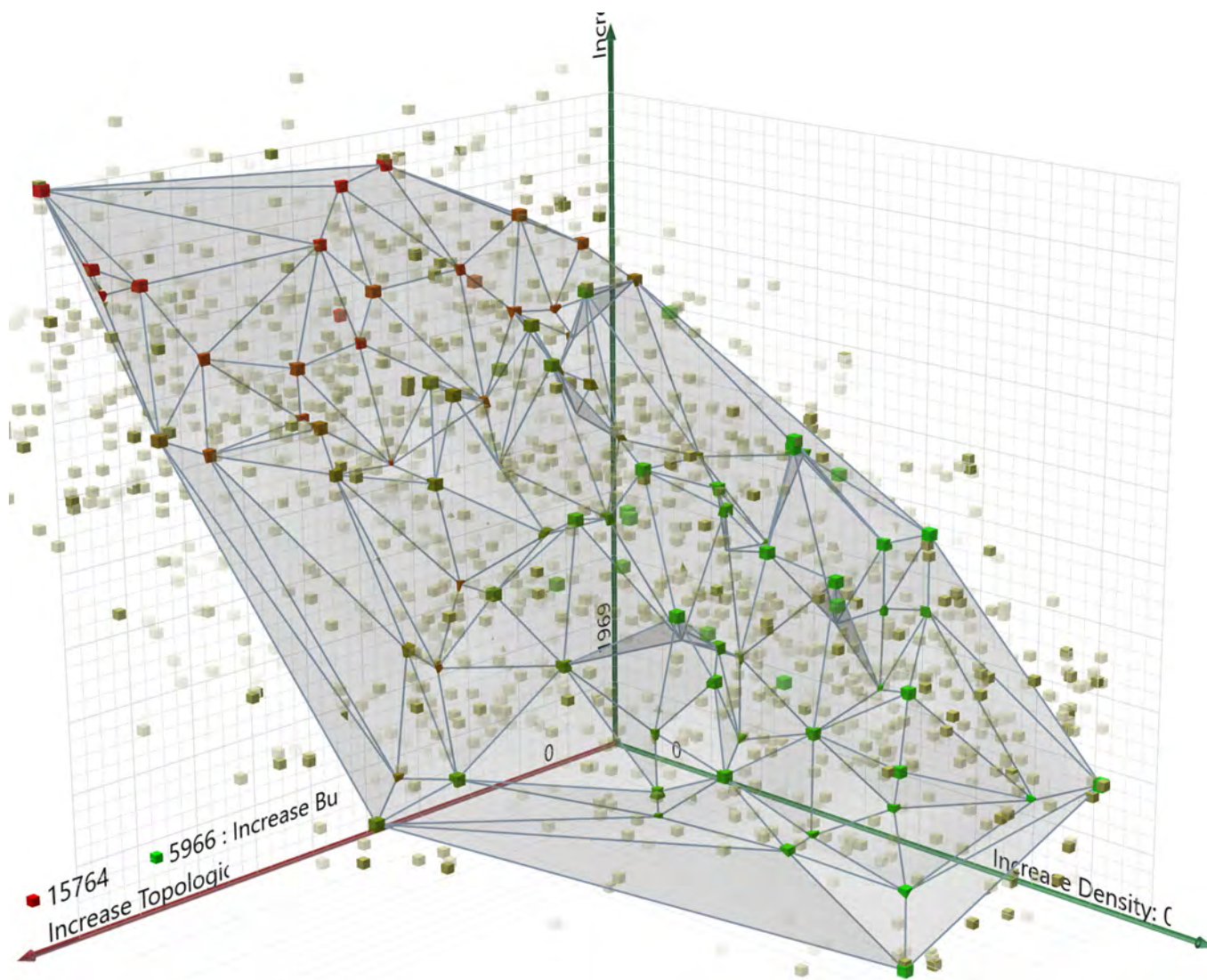


Figure 5.12.
The objective space of the entire population, and the pareto front of the final generation.

5.2.4. Analysis

The simulation ran 260 generations and evolved a population comprised from 26,000 solutions (figures 5.7. and 5.8.) ([Animation 3a](#)) in a time frame of 21 hours, in which the evaluation time per solution was calculated at approximately 2.9 seconds. Although this is significantly higher than previous experiments, the computational load was still very minimal; this was due to the way in which the phenotype's geometry was modelled using the least amount of mesh faces, and the utilisation of the surface division method developed in the previous experiment for a more streamlined solar analysis. The primary cause for the increase in evaluation time is attributed to the larger division of points on the phenotype, which was conducted in order to increase the efficiency of the solar analysis (both on the building envelope and on the ground surface).

The graphical analysis of the evolved solutions presented positive results in all 4 fitness objectives, with the most positive observed for the *connectivity* objective, while the least positive in the *density* objective. The results for each objective and their relation to one another is detailed below (figures 5.9.):

Connectivity:

The mean fitness increased incrementally throughout the simulation, with almost no fluctuations in the mean between the generation, indicating that the simulation is optimising the population towards a global (or very high local) optima. With regards to the variation of solutions, the standard deviation within each generation increased at the early stages of the simulation (indicating that the simulation was in an explorative state) before incrementally decreasing and then levelling off towards the end stages of the simulation. This corresponds to the analysis of the mean fitness trendline in which it indicates that the simulation was converging towards global optima.

Building Envelope Solar Gain:

Similar to *connectivity*, the simulation was able to incrementally increase the mean fitness from one generation to the next, however, the increase was less pronounced. In contrast, the variance within each generation incrementally increased throughout the entirety of the simulation. In both graphs, there is a degree of fluctuation between each generation, as the incremental increase (or decrease) is not as smooth as observed in the *connectivity* objective, indicating the presence of a somewhat noisy fitness landscape. However, this seems to be minimal as there is a clear trendline and directionality in both graphs.

Ground Solar Gain:

The standard deviations of generations evaluated for this criterion exhibit interesting results. At multiple times throughout the simulation (more so in the

early stages of the algorithm), there are multiple solutions in the population that are significantly different than the majority. The frequency of these solutions is minimal which indicates an anomaly has arisen in the design problem, in which the experiment generated a phenotype that is geometrically flawed, and so its analysis by the solver generates a highly unusual result. The degree of impact of these solutions is clarified through the analysis of the mean fitness chart, as the corresponding generations in which these solutions arise do not seem to impact the mean value of said generation, indicating that when these anomaly solutions arise, they do so at a very low rate, thus having very little impact on the generation (and the population in general). Moreover, due to the solver attributing very weak fitness values to these solutions (as can be observed in the fitness value charts), through the selection operator of the evolutionary algorithm, these solutions are culled from the population towards the later stages of the simulation, indicating the solver is not including such solutions in the pareto front (note: anomaly solutions are described in more detail in the following experiments).

Density:

From all the four fitness objectives, the density objective demonstrated the least improvement in its mean fitness throughout the simulation. Although there was an initial increase in the mean fitness at the early stages of the simulation, this levelled off and fluctuated around the same approximate value. In contrast, the variation within each generation was able to incrementally increase as the simulation progressed. The contrasting results between the variance and mean fitness indicates that the simulation is unable to converge towards a peak within the fitness landscape.

Through the analysis of the parallel coordinate plot, the solutions that exhibited the most repeated fitness values were extracted and their location identified in the population. According to the numerical data generated, the *solar gain* objective demonstrated the most repeated fitness values, in which a total of 39 solutions exhibited the same fitness. Interestingly, these solutions emerged at multiple stages in the simulation run (rather than at later stages), which indicates that although the solver attempted to find a solution with better fitness values, (and indeed did on countless occasions), it also repeatedly generated solutions that were less fit, which indicates that the solutions for the solar gain fitness objective converged (figures 5.10, 5.11. and 5.12.).

5.2.5. Conclusions

The independent analysis of the four criteria, and their association to one another indicates that three of the criteria, *connectivity*, *ground solar exposure* and *building solar exposure* complement one another, while the fourth criteria, *density*, is in heavy conflict with the rest (this is confirmed through the analysis of the diamond fitness charts). It was assumed that density

and building solar gain would optimise in favour of each other, (as increasing density would generate more building surface for solar gain), however, due to the low sun angle imposed in the design problem, higher buildings generate significant overshadowing on both ground and adjacent buildings, therefore to avoid this, the simulation preferred reducing density in favour of solar gain. Despite the above, there is significant morphological variation between solutions of the final generation, in which there are phenotypes that exhibit traits suitable for each of the four criteria. This is supported by the relatively equal distribution of solutions in the objective space and pareto front ([Animation 3b](#)).

Interestingly, although the original phenotype was constructed through a combination of the 'courtyard block' and the 'tower block'; by the final generation, the simulation has evolved a solution set that has completely removed the presence of the tower blocks. This is similar to experiment 1B, where the simulation evolved a solution set that was primarily driven towards blocks with towers. This indicates that the simulation is capable of maintaining variation between solutions within a generation (regional variation) while simultaneously driving the population towards either favouring (such as in experiment 1B) or discarding (such as in experiment 3) a specific morphological trait.

Additionally, even though the simulation repeatedly evolved solutions with the same fitness value, further analysis of each of these repeated solutions indicates that the convergence of one fitness objective did not cause the other fitness objectives to converge. This demonstrates that it is essential not to conclude that phenotypes with the same fitness values for some objectives are automatically the same for all objectives; it is possible for the simulation to simultaneously converge for some objectives while also maintaining variation.

A limitation of the experiment conducted (and in experiments 1 and 2) is that the size of the superblock (i.e the number of blocks within it) and the complexity of the design problem were limited to how the gene sequences were applied to the phenotype's body parts. In all previous experiments, the genes were applied to the 3dimensional geometry of the phenotype; in doing so, the computational load dictated that the blocks within the superblock *could not* intersect (due to the heavy process of conducting booleaning operations between two geometries). This significantly limited the variables that acted on (and constructed) each phenotype. Therefore, in addition to advancing the methods applied so far, and examining the formulation of the design problem through an opposing environmental and geographic location, the following experiment examines methods to avoid (or delay) constructing the 3dimensional representation of the phenotype in order to allow for the blocks within each super block to intersect with one another, which should ultimately allow for the design problem to utilise a larger superblock.

5.3. Experiment 4 - Fes El Bali

5.3.1. Ambition

Experiment 4 consolidates all of the tools and methods developed in the previous experiments, as well as taking into account the achievements and limitations encountered thus far, to formulate the final design problem presented in experiment 4. Similar to experiment 3, the design problem addresses the environmental stresses faced within the selected location, the city of Fes El Bali, which in the context of the experiment conducted, are issues of climate, density, connectivity and open space. Additionally, the experiment completely reformulates the method by which the superblock is constructed, focusing more on the 2d representation of the geometry (and applying the genes to this 2d representation) rather than its 3d representation (which was the approach conducted in the previous experiments). Consequently, this allows for a significant increase in the size of the superblock when compared to the previous experiments conducted.

Before presenting the experiment setup, the following section examines issues of higher-level connections between blocks within the superblock, upper level open spaces and ground level open spaces, as well as provide a historical account of the city of Fes; all of which will eventually dictate the genes, body parts and fitness objectives to be formulated within the design problem.

5.3.1.1. Higher-level connections

The morphology of cities and the efficiency by which they grow and occupy their environment has gained significant attention (Batty and Longley, 1994). The current urban morphologies developed through lateral growth and centralised nodes of activities have two conflicting objectives; first to be as compact as possible – centralization; and second to be as dispersed as possible – decentralization (Batty, 2013). In recent years, the dramatic increase (and projected future increase) of urbanised populations has placed an overwhelming demand on the world's existing cities (both in terms of space and resources). Although the impact of this naturally leads to verticality, this has been implemented within the scale of a single building, yet the city's flow continues to grow laterally at ground level. As a result, the programs which are parasitic to this system are being distributed at street level while buildings continue to develop as separate entities vertically. This led to Harvey Wiley Corbett, primarily known for his skyscraper designs, to be one of the first figures to suggest in the early 20th century the integration between multi-level street networks and mixed-used skyscrapers (Goodman, 2008).

Patterns of settlements in many urban areas are transforming from dispersed fabrics to centralised entities with integrated infrastructures (Kern, 2007). In most cases, their application is in the form of segregated and standalone buildings comprising multiple functions. However, in cities like Hong Kong, Minneapolis and Calgary, the application of higher-level connections has been proven to benefit the urban context. In Hong Kong; traffic congestion, vehicle and noise pollution are the reasons for the incorporation of high-level connections within the urban block. While in Minneapolis and Calgary, their application was in response to the region's harsh climatic

conditions, leading to an 18km network of higher-level connections throughout the urban fabric. In addition to their climatic advantages, Corbett et al. (2009) argue that such connections allow for greater and more efficient circulation paths across the urban landscape. The term *Skyway* refers to connections at upper levels between the built environments within the urban block; the emergence of such connections allows the spaces required for these circulatory systems to appear at higher levels across the urban fabric, eventually leading to the formation of multi-level networks of connections across the city.

5.3.1.2. Vertical Distribution of Public Space

The physical and social structures of a city have a reciprocal influence on one another as they continue to develop (Batty, 2013). Interactions between individuals happen at different scales and locations within a city. However, these networks of interactions are not constrained to their physical structures, but the variation of such dynamic interactions is surpassing the current physical attributes of cities. Public spaces across the city are examples of such areas, where the spatial structure facilitates the social interactions of its inhabitants. The majority of public spaces accessible to the public are located at the street level, while the network of interactions goes beyond a singular level.

Vertical development resulting from technological advancements and coupled with the shortage of land availability has gained ground in recent years. Cities like Hong Kong and Manhattan are examples of such developments. However, their verticality is applied at the scale of single isolated buildings rather than at the level of the urban fabric, the result of which refrains the distribution of public space to extend beyond the street level. More importantly, these areas have emerged as 'leftover spaces' between the isolated verticality of single blocks. Thus, the experiments presented examine the distribution of public spaces on multiple levels. In addition to this, rather than emerging as a by-product of the relationship between blocks, the experiments designate a distinct identity to such spaces, allowing for their propagation throughout the urban fabric.

One of the current models for the development of urban forms— *the urban sprawl*; according to Michael Wegner and Frans Dieleman (2004) has unintentional consequences, primarily the loss of open space. By allowing the vertical development and distribution of public spaces, the urban fabric and its organizational structure would transform conventional urban morphologies. Although an urban patch may be constrained to its physical boundaries at ground level, thus limiting the development of public space, the vertical distribution of such spaces bypasses this constraint. Such spaces have great potential to be considered not as isolated rooftops but as a network of spaces connected to one another through skyways. The experiments presented examine the advantageous and disadvantageous of such spaces within the urban landscape.

5.3.1.3. Neighbourhoods, Territories and Ecology

The demands imposed by the changing environmental and climatic conditions coupled with a growing demographic has challenged cities' ecological capabilities to adapt to these changes; while the stresses of energy consumption have significantly affected cities' internal environmental and ecological contexts. Although the processes associated with urban variation and development play a pivotal role on the ecological impact on both the local and regional environments, further analysis of these processes necessitates approaching ecological systems as dynamic models, ones that continuously explore and adapt to changing social patterns and biophysical properties. An urban ecological model is integral to adaptability, change and flexibility.

In contrast to many of the planned cities of the 20th century, evolving cities have been closely coupled to their immediate territories; with distinct morphologies, integrated infrastructure and urban cultures that have evolved in response to the specific ecological and climatic conditions of the region. As these cities grow and develop in complexity, they have become less dependent on their immediate surroundings by drawing the required energy demands from their local territories (Weinstock, 2010).

From this perspective, it has been argued that cities are analogous to living organisms; systems that consume resources and expel their by-products, leading to the notion that urban tissues behave with a high degree of metabolic properties. The term 'urban metabolism' has been prescribed to urban fabrics that transform materials into infrastructure, human biomass and waste; bearing a significant impact on the environmental and climatic conditions that extend beyond the city's limits (Wolman, 1965). In this regard, the goal of urban metabolism is to optimise the metabolic processes of the city by addressing resource generation through an intelligent ecological infrastructure that is integrated within the urban fabric. Therefore, the city's morphology and configuration are crucial in reducing its carbon footprint while simultaneously increasing its responsiveness to a changing environment. This is achieved through integrating the ecological infrastructure within the city rather than isolating it to a locale that falls outside the city's territory. More importantly, its integration as part of the urban morphology is critical to increased efficiency of resource extraction and consumption; features that are essential for the urban fabric.

5.3.1.4. The Medina of Fes

The Medina of Fes (or Fes el Bali), located in the north-eastern region of Morocco, has been listed as a world heritage site by UNESCO in 1981 for the perseverance and influence of its history, culture, architecture, urban landscape and heritage throughout the past millennia to modern day (UNESCO World Heritage Centre, 2018). The *medina* is characterised through a unique urban landscape; a highly compact and dense distribution of 2 – 4 storey blocks and superblocks that synthesise the city's Islamic culture and heritage through inward looking courtyards. It is this association between the Islamic culture's value of privacy, and the morphological distribution of blocks within the city that defines one of the most intriguing traits of the medina; the differentiation yet seamless relationship between private, semi-private and public spaces distributed throughout the urban tissue.

The irregular distribution of blocks and superblocks within the city has resulted in the medina being appropriated with a highly pedestrianised urban landscape. Vehicular traffic is limited to a small number of streets, while the majority is allocated to foot traffic. The hierarchical differentiation between public and private continues to manifest itself through the medina's street network, where streets vary significantly in width which in turn reflects the requirement for privacy (or openness) within the public spaces. More importantly, the irregular distribution of blocks coupled with the varying street network holds a significant impact on the solar gain on street level, with many of the streets lying in shade due to the irregular morphological distribution throughout the urban tissue (Johansson, 2006).

As with many cities throughout the world, the city of Fes is experiencing increasing rates of population growth within a very short time frame. The city's population has almost tripled in size since the medina has been listed as a world heritage site in 1981, with the impact of the increasing population affecting the medina's urban fabric and sprawl (El Garouani et al., 2017). In addition to generating considerable stresses on the environment and resources of the medina, the city's stakeholders have been impacted by the struggle for a continuously decreasing supply of land, with a direct competition between residents, small business owners and large businesses; each fighting for their space within the city. The following experiment attempts to reconfigure the morphological and urban distribution of the medina to address issues of climate, ecology and city context while simultaneously maintaining the original morphological characteristics of the city's superblocks which have persisted across millennia (figure 5.13.).



Figure 5.13
Medinah of Fes El Bali from
above (Mikko, 2015).

5.3.2. Experiment Setup

The urban conditions described above of vertical connectivity between urban blocks, elevated public spaces, neighbourhoods, territories, ecological context and the control of solar gain on ground level to increase solar comfort are incorporated as fitness objectives to which the primitive (the Fes superblock) will aim to optimise for. Throughout the evolutionary simulation, the different urban forms will be evaluated (both statistically and morphologically) in an attempt to highlight emergent behaviour among the evolved solutions at either the level of a single superblock, or between superblocks across multiple generations. The experiments will present these behavioural traits through the analysis of individual solutions extracted from different generations throughout the simulation and a comparative statistical analysis of every 100th generation (figure 5.16.).

5.3.2.1. Constructing the Phenotype

Utilizing the urban block of the city of Fes in Morocco as the basic geometric component (Figure 5.14.), the primitive's size is significantly increased from previous experiments, in which the phenotype is comprised from a 10x10 superblock, i.e. 100 blocks (Figure 5.15.). This expands on the previous experiment whose phenotype comprised from 16 blocks (4x4).

The objective of the experiment is to generate a population of superblocks that attempt to optimise for the following fitness criteria: a) an increase in the area of neighbouring open spaces around each block cluster (Figure 5.17.) an increase in the area of elevated public open spaces and walkways (Figure 5.18.) an increase in the distance between upper and lower level open spaces (Figure 5.19.), and d) a decrease in solar exposure on street level. Each of these objectives are directly correlated to morphological transformations used to construct the form of each superblock; therefore, the regulation between the genes, fitness objectives and body part is given through the method in which the superblock is constructed.

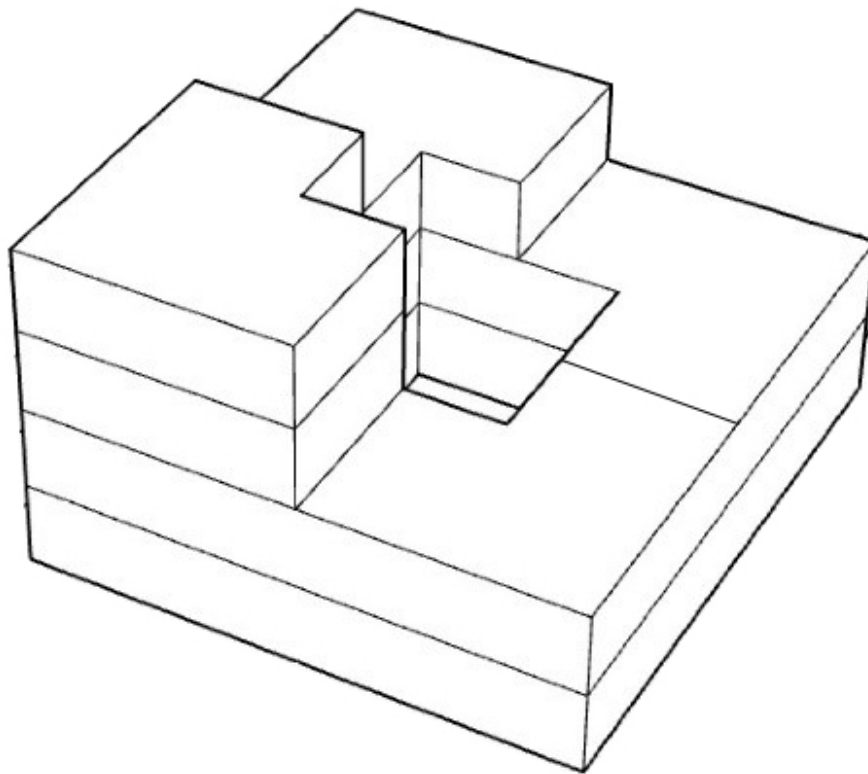
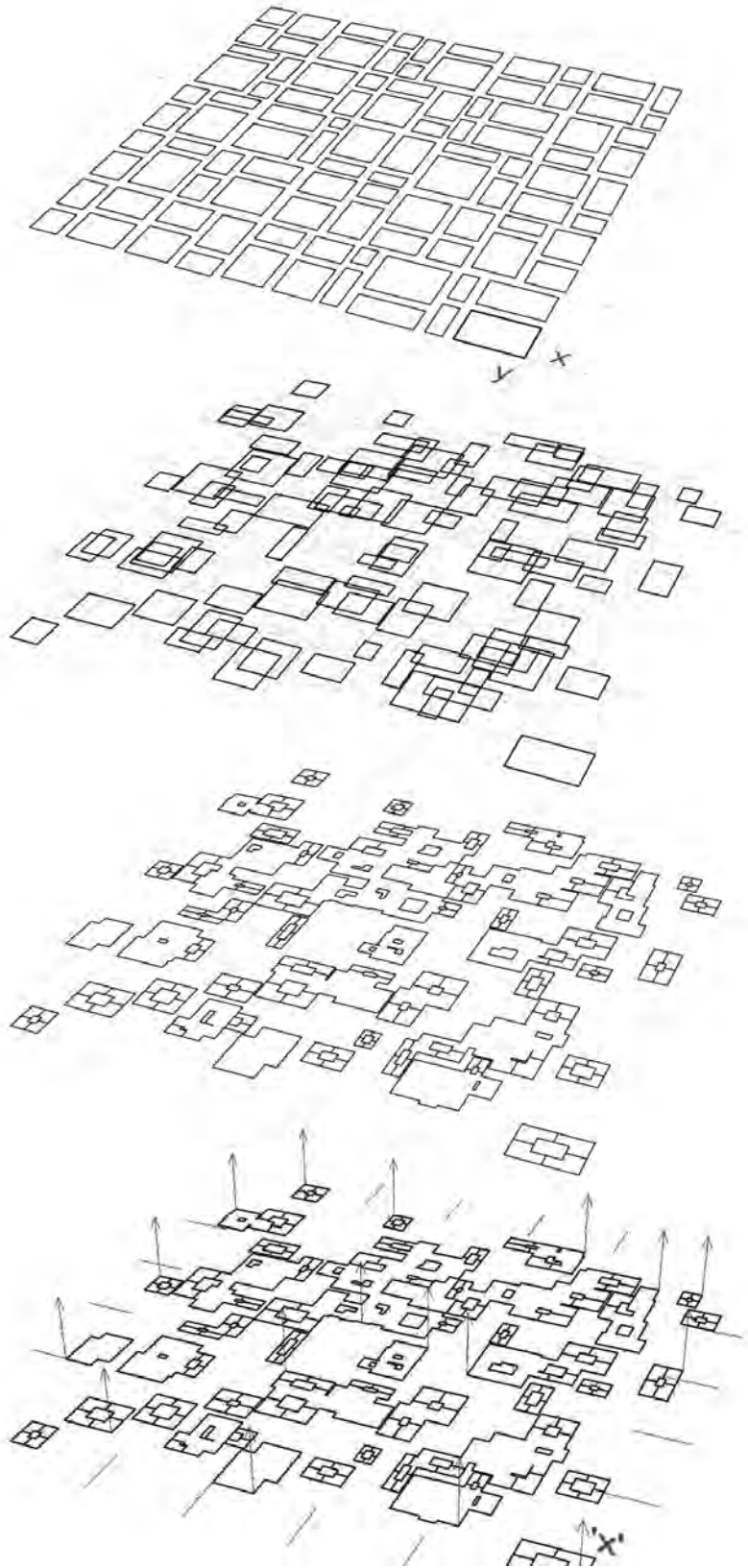
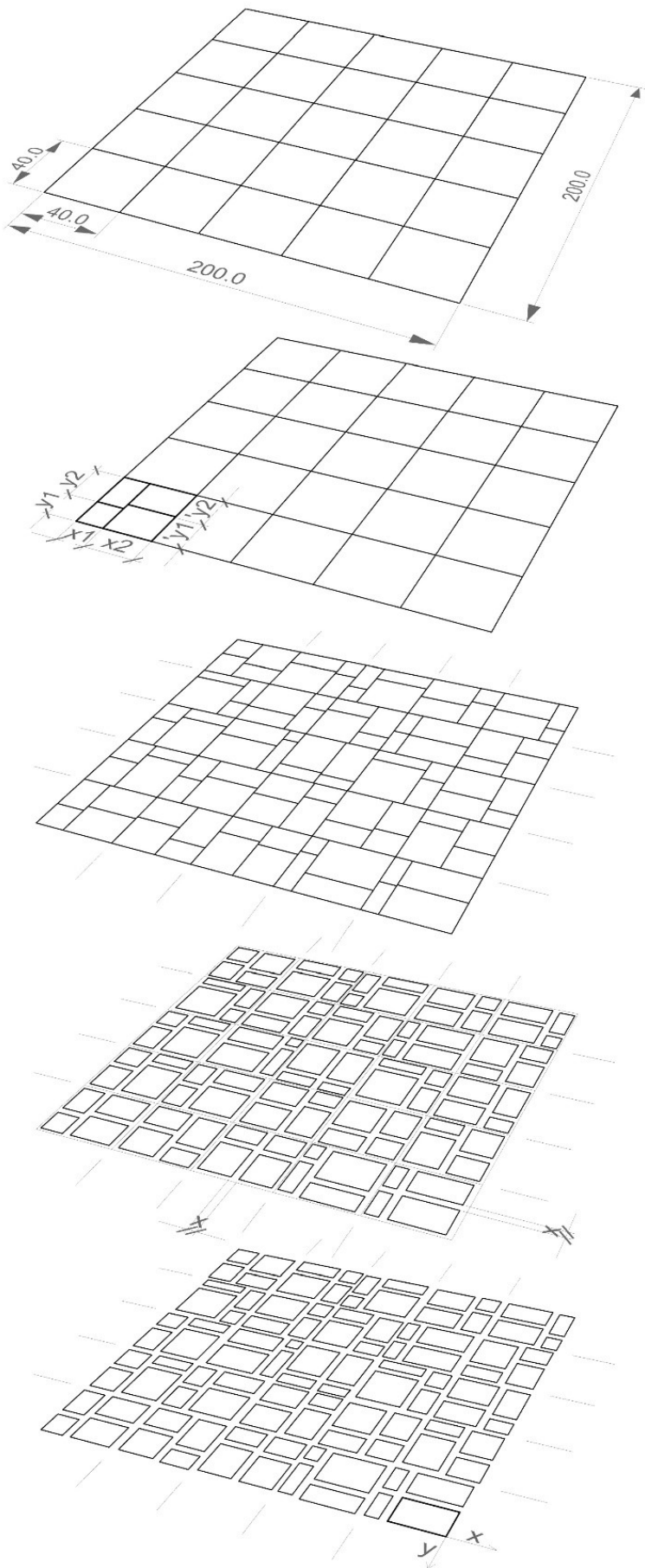


Figure 5.14.
The Fes Urban Block



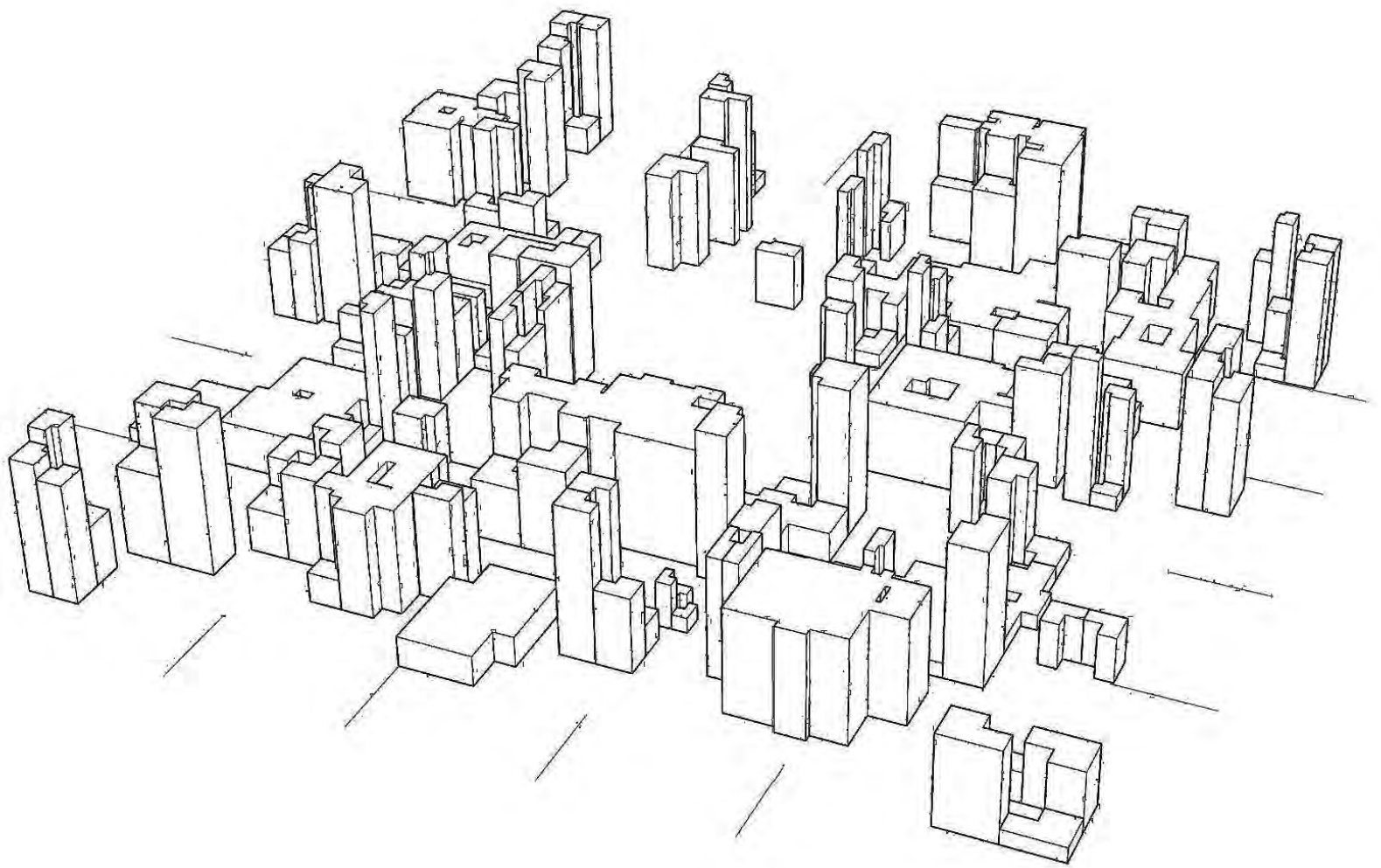
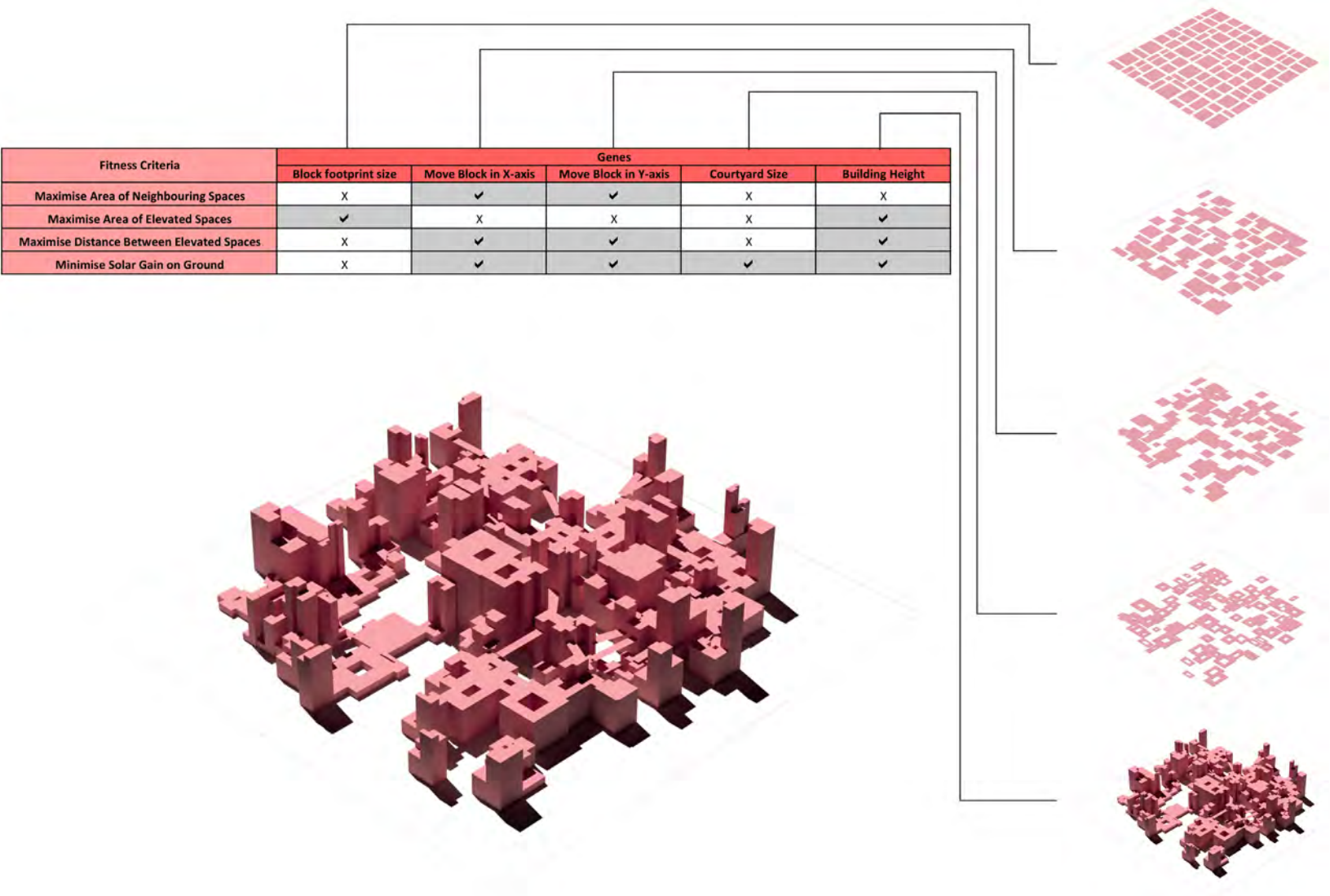


Figure 5.15.
Constructing the Superblock.

Goal	<i>Generate an urban superblock that addresses environmental and demographic stresses of the city of Fes El Bali through incorporating within it elevated open spaces and connections. Through maximising the superblock size and a 2dimensional formulation of the design phenotype, generate morphological variation through the formal intersection of adjacent blocks within the superblock.</i>
Objectives	<ul style="list-style-type: none"> • <i>Generate connections between blocks on upper levels</i> • <i>Break the linearity within the superblock</i> • <i>Increase number of rooftop open spaces</i> • <i>Generate clusters of open space on ground level</i>
Fitness Criteria	<ul style="list-style-type: none"> • <i>Maximise area of neighbouring spaces</i> • <i>Maximise area of elevated spaces</i> • <i>Maximise distance between elevated spaces</i> • <i>Minimise solar gain on ground</i>
Phenotype	<i>10x10 superblock comprised from the typical Fes El Bali block</i>
Gene Pool	<ul style="list-style-type: none"> • <i>Size of block footprint</i> • <i>Move block in X-Axis</i> • <i>Move block in Y-Axis</i> • <i>Change in courtyard size of each block</i> • <i>Change heights of each building unit within a block</i>

Figure 5.16.
Design Problem – Experiment
4: Summary of the design
problem and description of
how the fitness objectives,
gene sequences and body
parts regulate each other.



Buildings in the urban patch cluster around each other based on their proximity and form neighbourhoods in the phenotype. These neighbourhoods may overlap or even share common ground. Unlike in the previous experiment where overlapping geometry was avoided at all costs due to the computational load incurred by the booleaning operations, a method was developed in this experiment in which the entirety of the transformations on the phenotype were imposed on the curves of the geometry rather than their extruded counterparts. Therefore, the need for booleaning of 3d geometry was replaced with simple 2-dimensional unioning/subtraction of planar curves. This played a highly critical role in defining the phenotype, as without it, the design problem would have required significant simplification (thus foregoing many of the objectives that are being investigated). Through applying the unioning/subtraction operators to the geometry, in which the footprint of the built areas was subtracted from the neighbourhood boundary, the superblock's open spaces are defined. *The adjacent open spaces* within a neighbourhood in the context of this paper refers to designated spaces available to each neighbourhood within its territory (Figure 5.17).

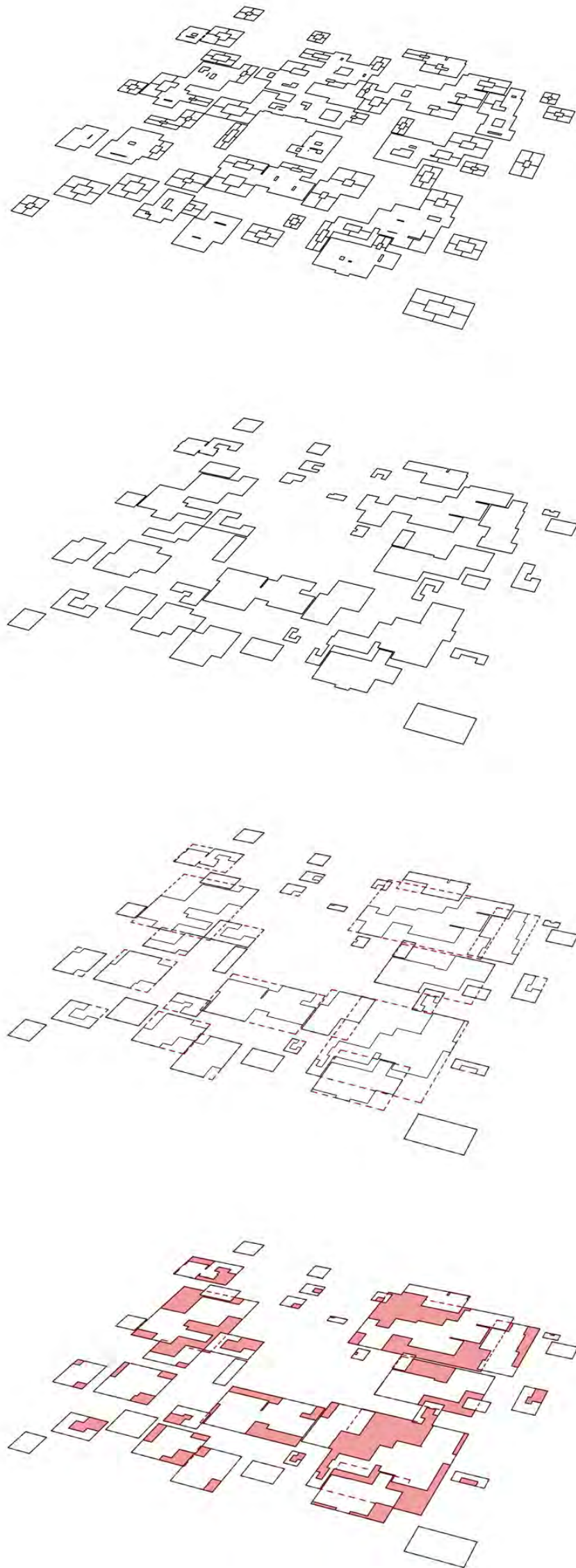
The significance of networks and public spaces on upper levels throughout the urban fabric has been discussed in previous sections; thus, the superblock is constructed to allow the phenotype to develop these spaces and connections should the algorithm favour such solutions, allowing for greater numbers of public spaces that are not bound to the street level. This is achieved through an analysis conducted within the design problem that selects roof spaces with a footprint that is above a certain threshold (in the case of the experiment conducted, the threshold was set at 800 sq.m) and connects these roof spaces to their neighbouring buildings. As the rate of upper level spaces increases, the simulation is driven towards increasing the connectivity amongst them by initiating upper-level walkways throughout the superblock (Figure 5.18). This also ensures circulation and movement are not constrained to the street level.

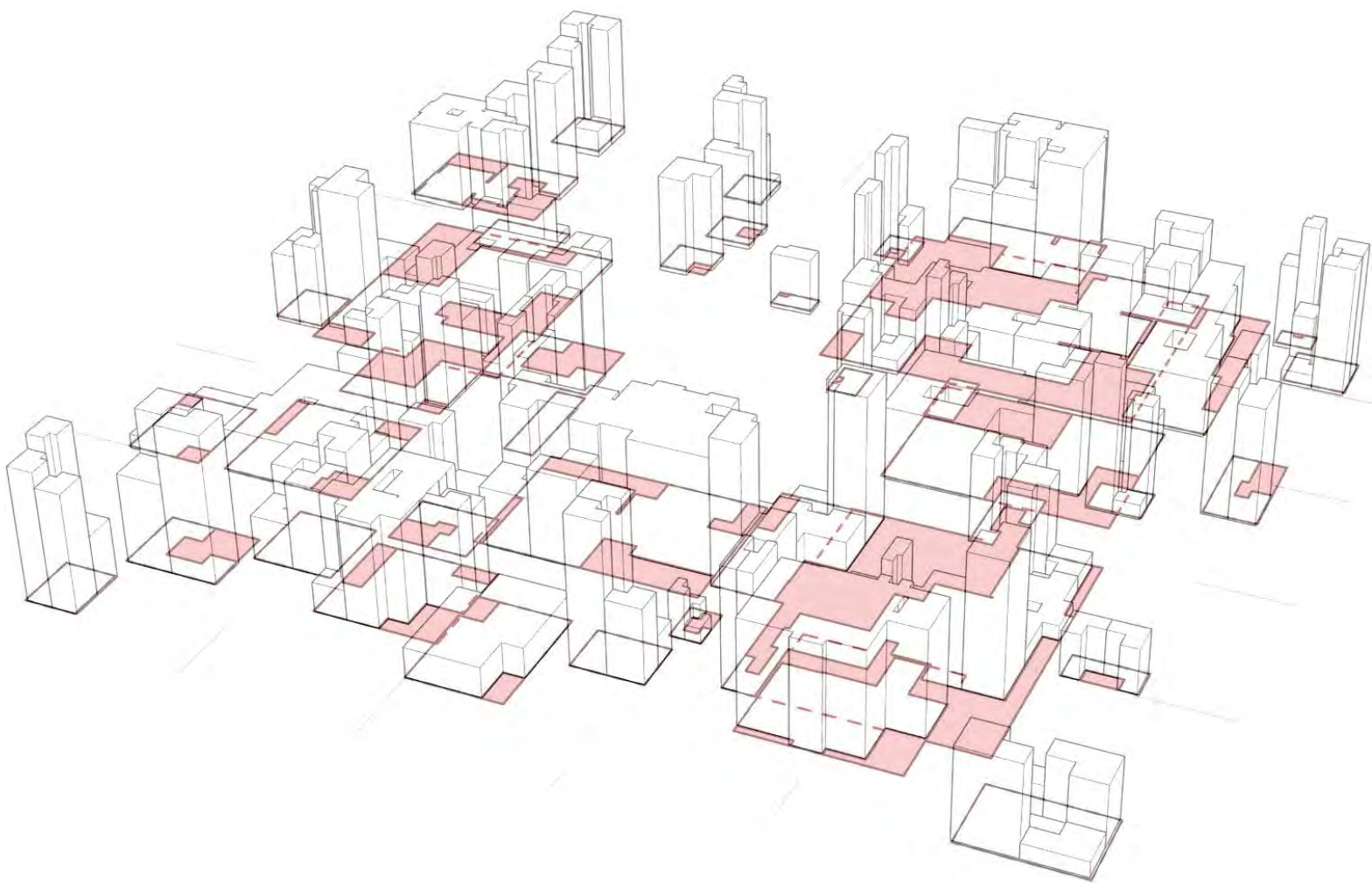
By increasing the distance between open spaces, their accessibility from various parts of the superblock is increased, allowing for greater connectivity to these spaces while simultaneously encouraging verticality rather than horizontality (Figure 5.19). Finally, decreasing the solar exposure on the ground level ensures high degrees of overshadowing and allows for greater distribution and clustering of the blocks within the superblock (Figure 5.20).

To accomplish this, various transformations control the phenotype's morphology through modifications that comprise moving the initial boundaries of the primitive in the XY plane, in addition to changes in courtyard sizes, building heights and dimensions. In addition to this, the transformations also allowed for the emergence of connections between selected blocks and their respective elevated open spaces. The relationship between the blocks and the open spaces is driven by a fall off area attributed to each elevated open space.

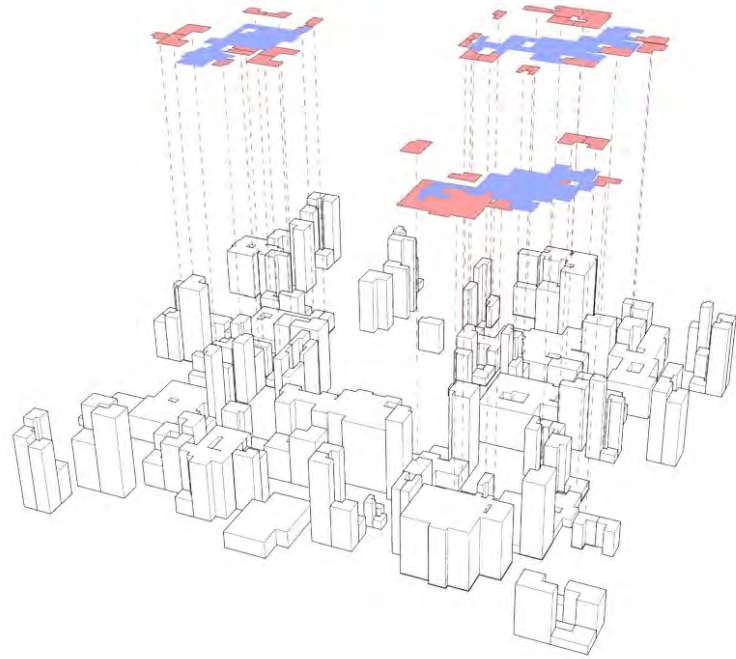
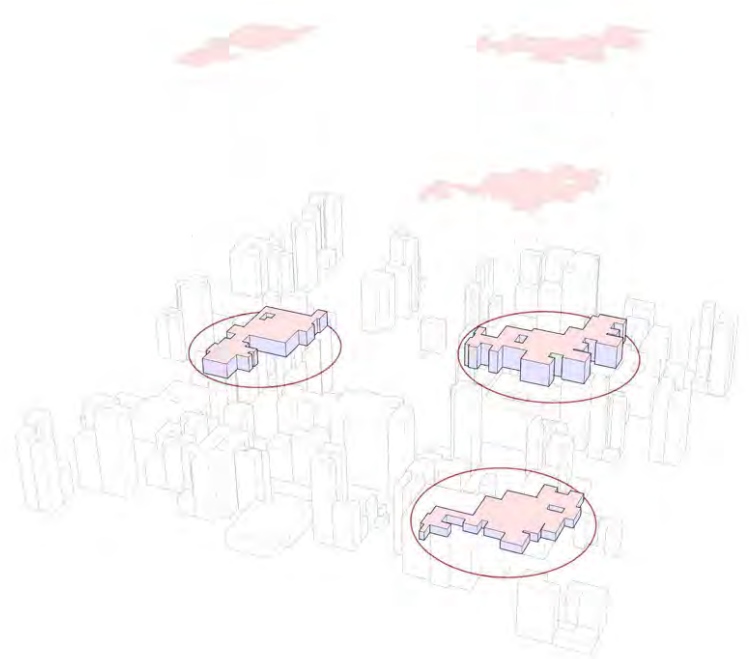
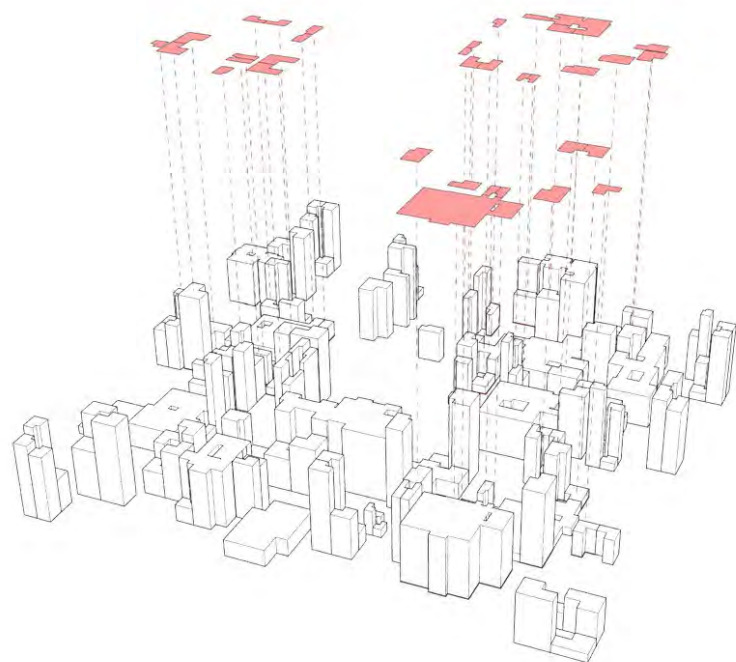
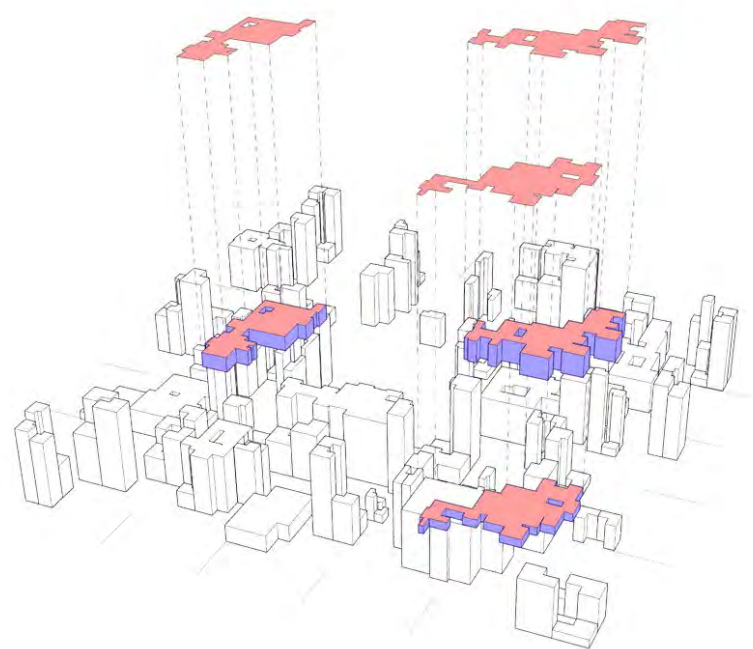
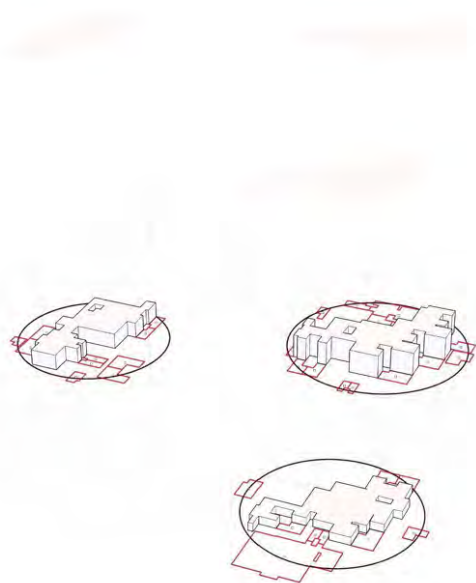
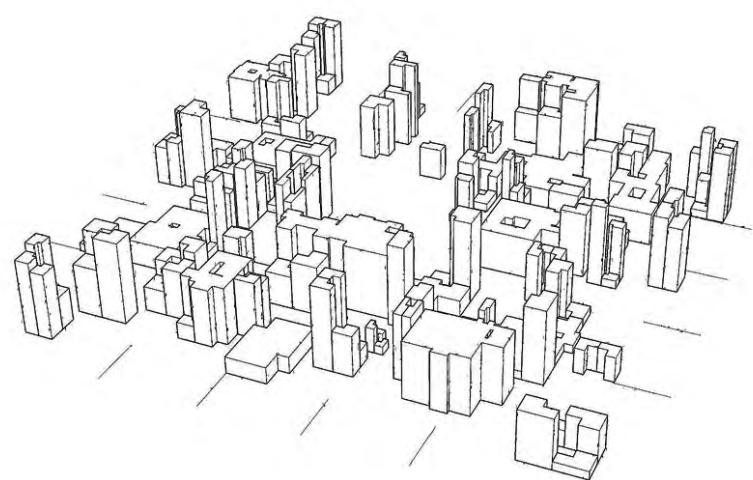
5.3.2.2. Solver Parameters

Finally, and in contrast to the previous experiment, the generation size defined for the simulation was set at 25 solutions per generation, while the generation count was set at 1000 generation. Accordingly, and in response to the low generation size, the algorithm parameters were set to reduce the mutation rate at every generation while simultaneously increasing the mutation probability. A low generation size and a higher generation count translates to an increased number of crossover operations to occur, thus increasing the likelihood for smaller, beneficial mutations to spread throughout the population. Thus, the solver parameters were set as the following: Mutation Rate – 25 %; Mutation Probability – 20 %; Crossover Rate – 80% and Elite Size at 50%.



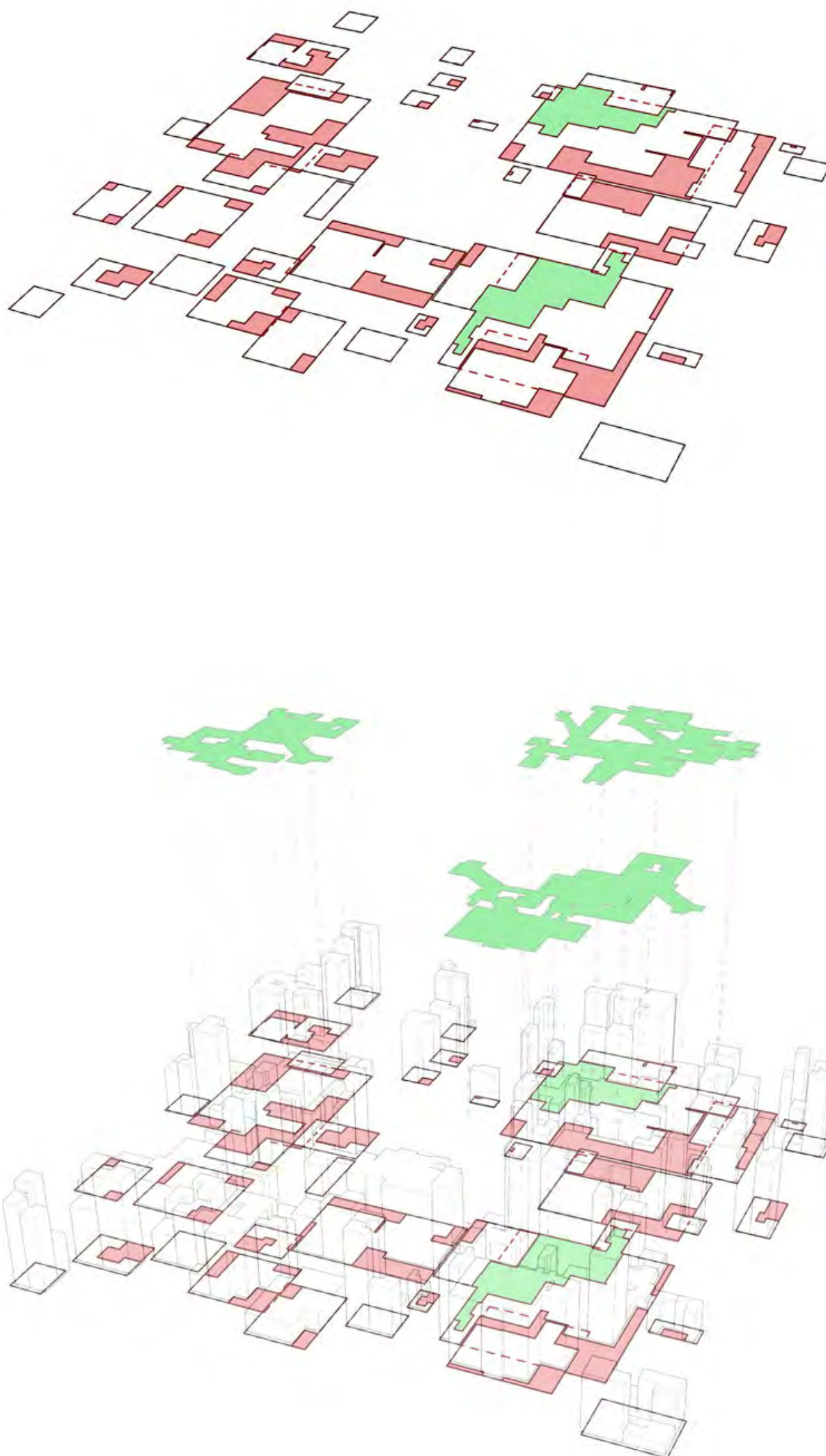


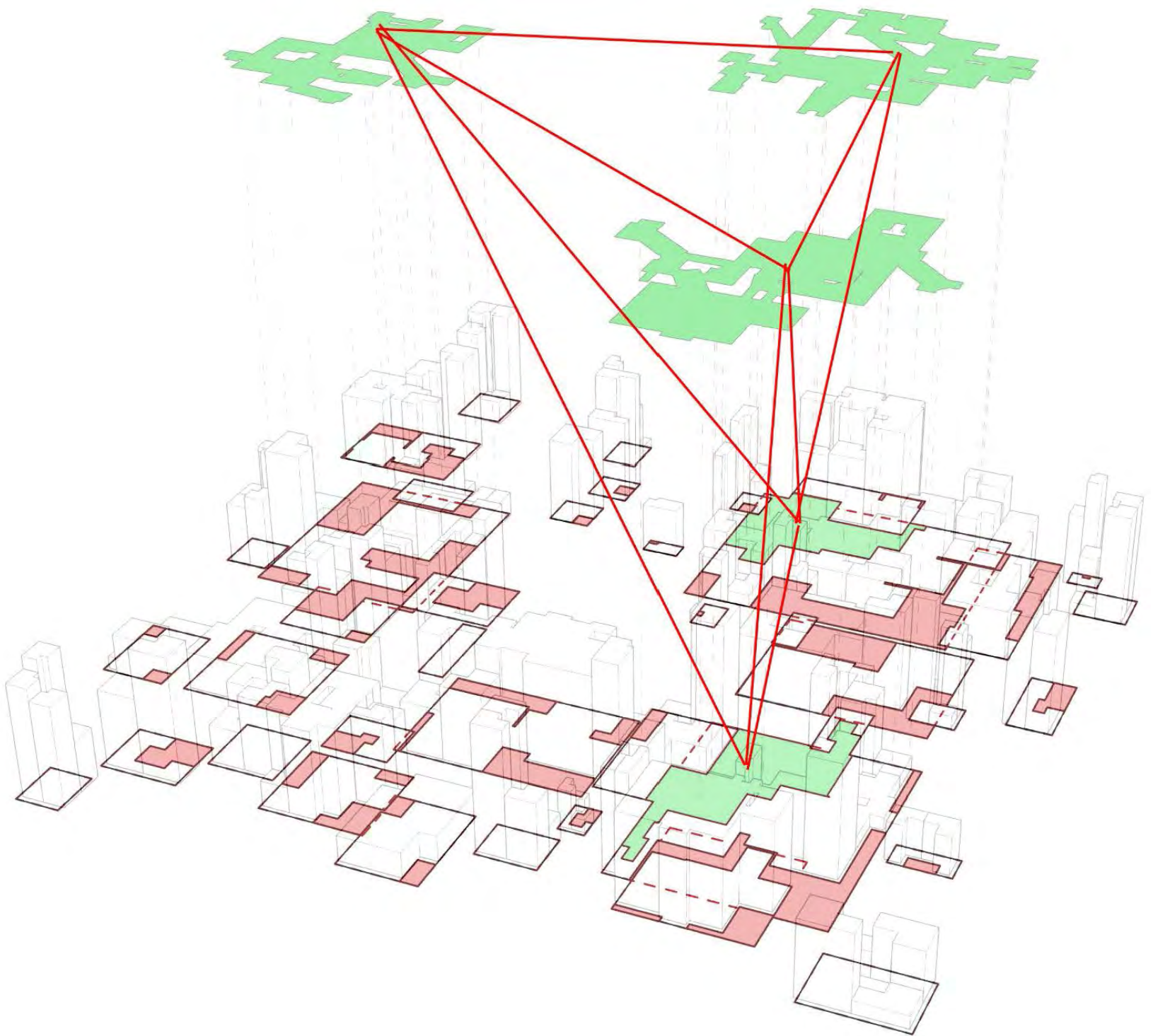
5.17.
Calculation of the
neighbourhood spaces





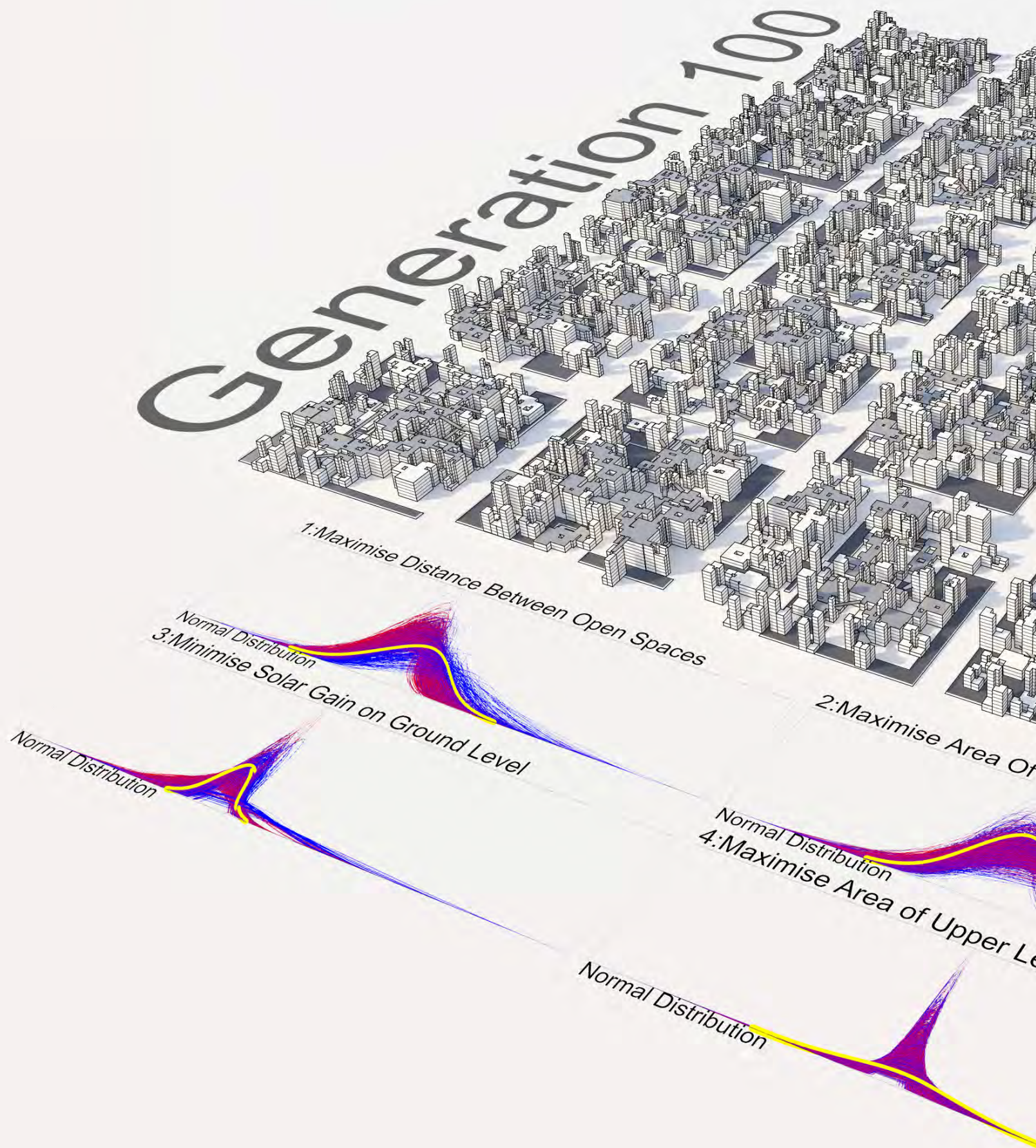
5.18.
Calculation of the upper level
spaces





5.19.
Calculation of distribution
between all open spaces

5.3.3. Outcome

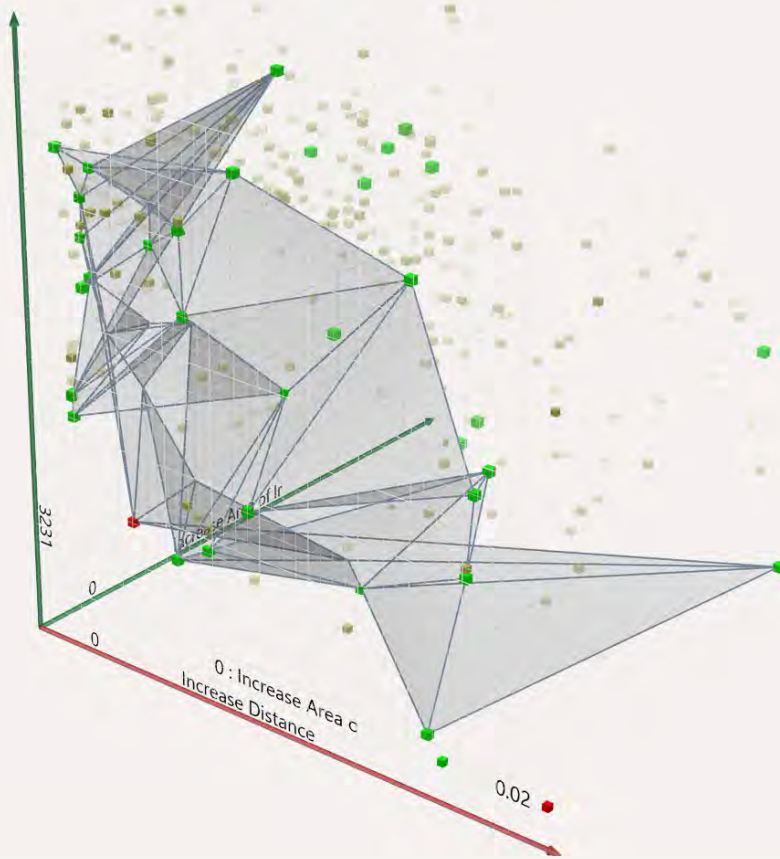


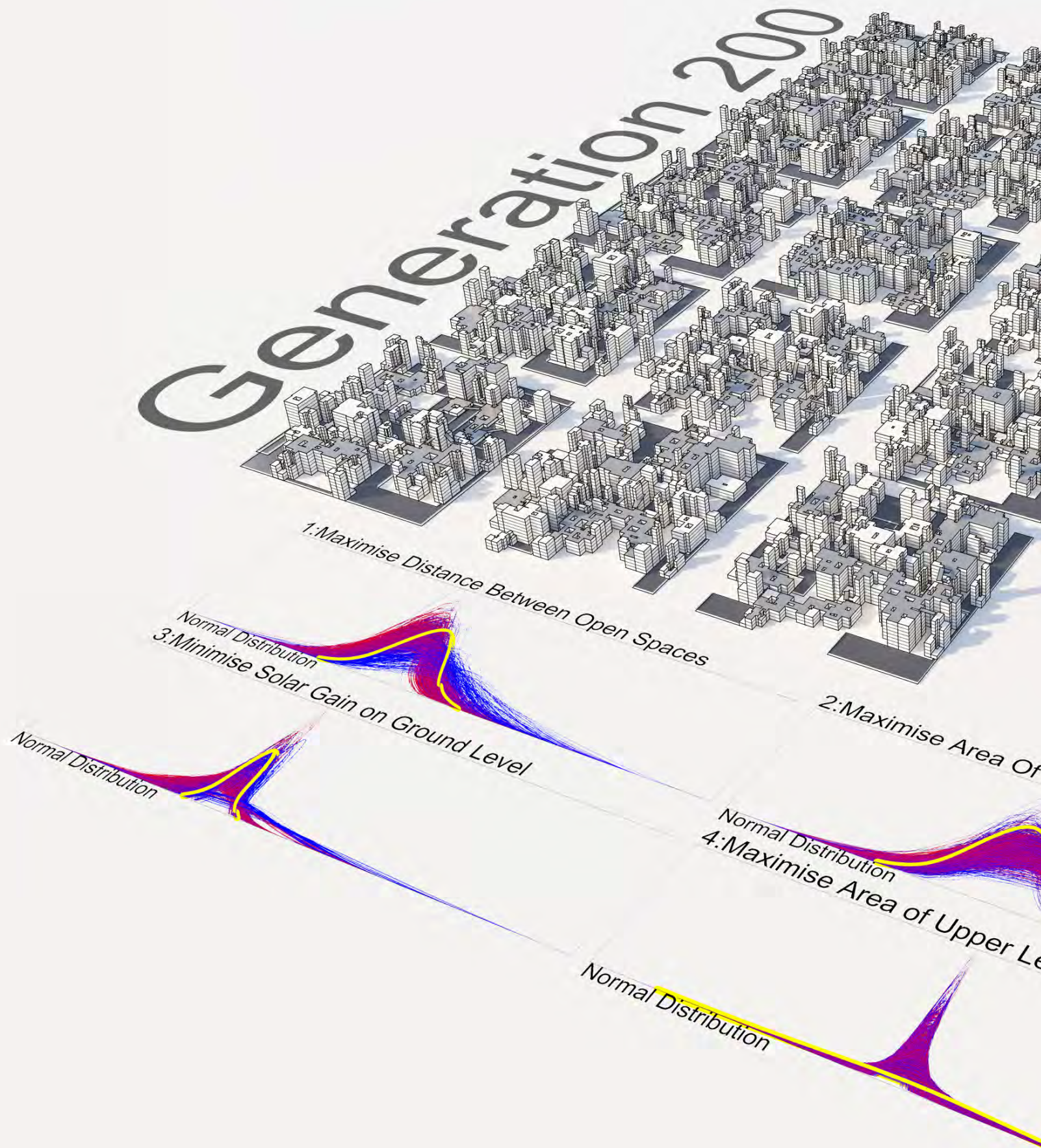
5.20.
Phenotypes and graphical
analysis of generation 100.



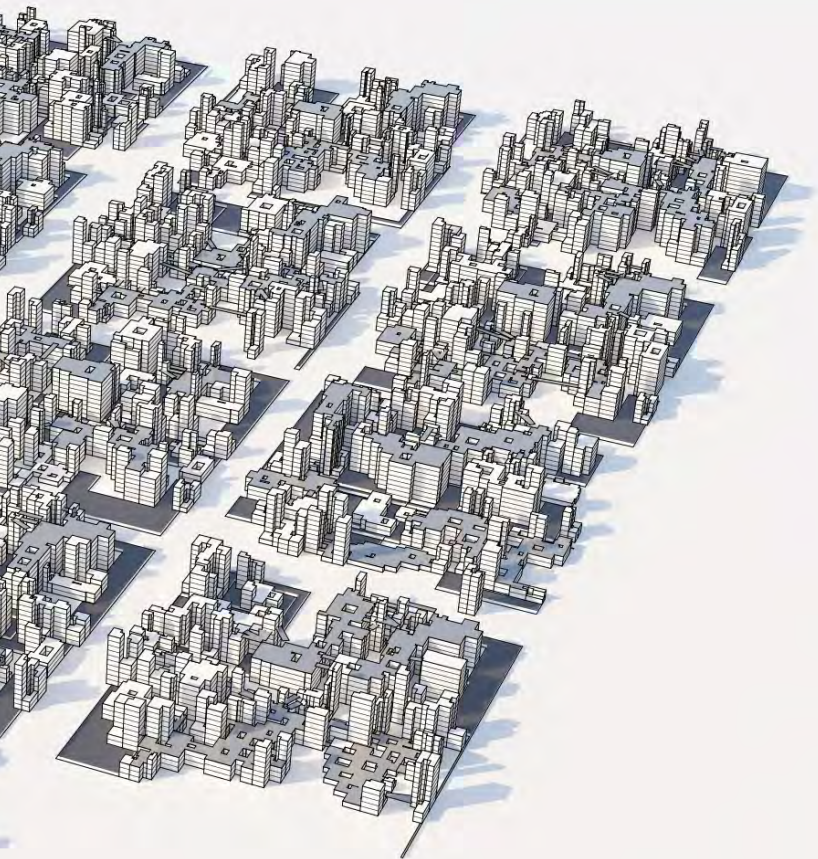
Immediate Open Spaces

Level Spaces



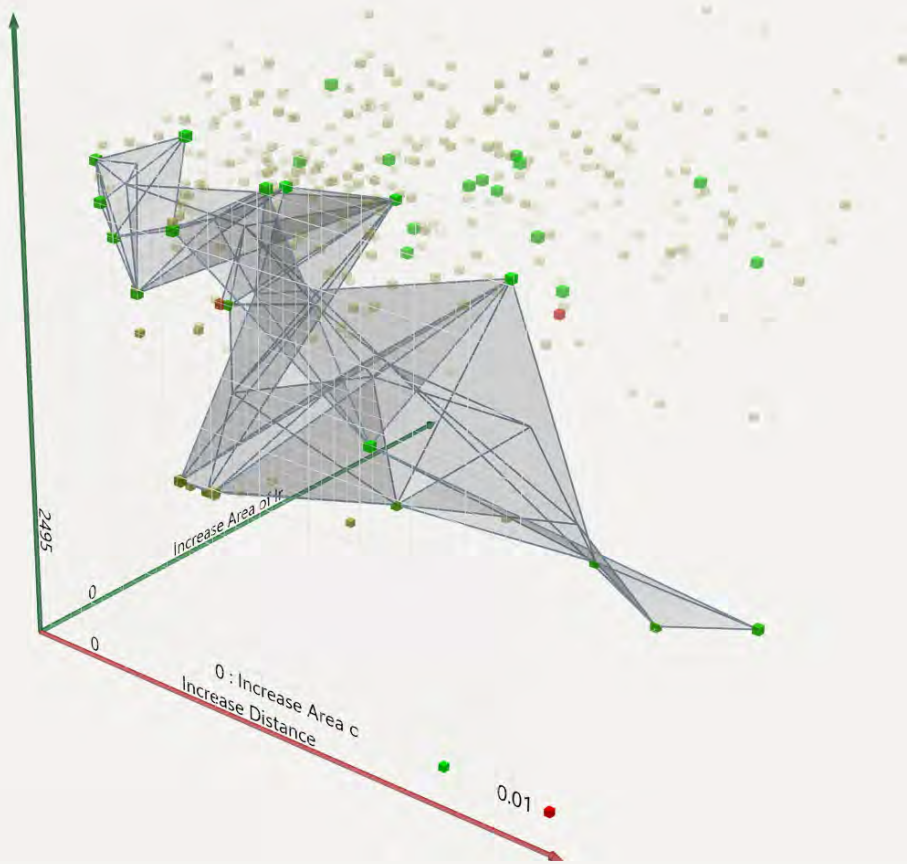


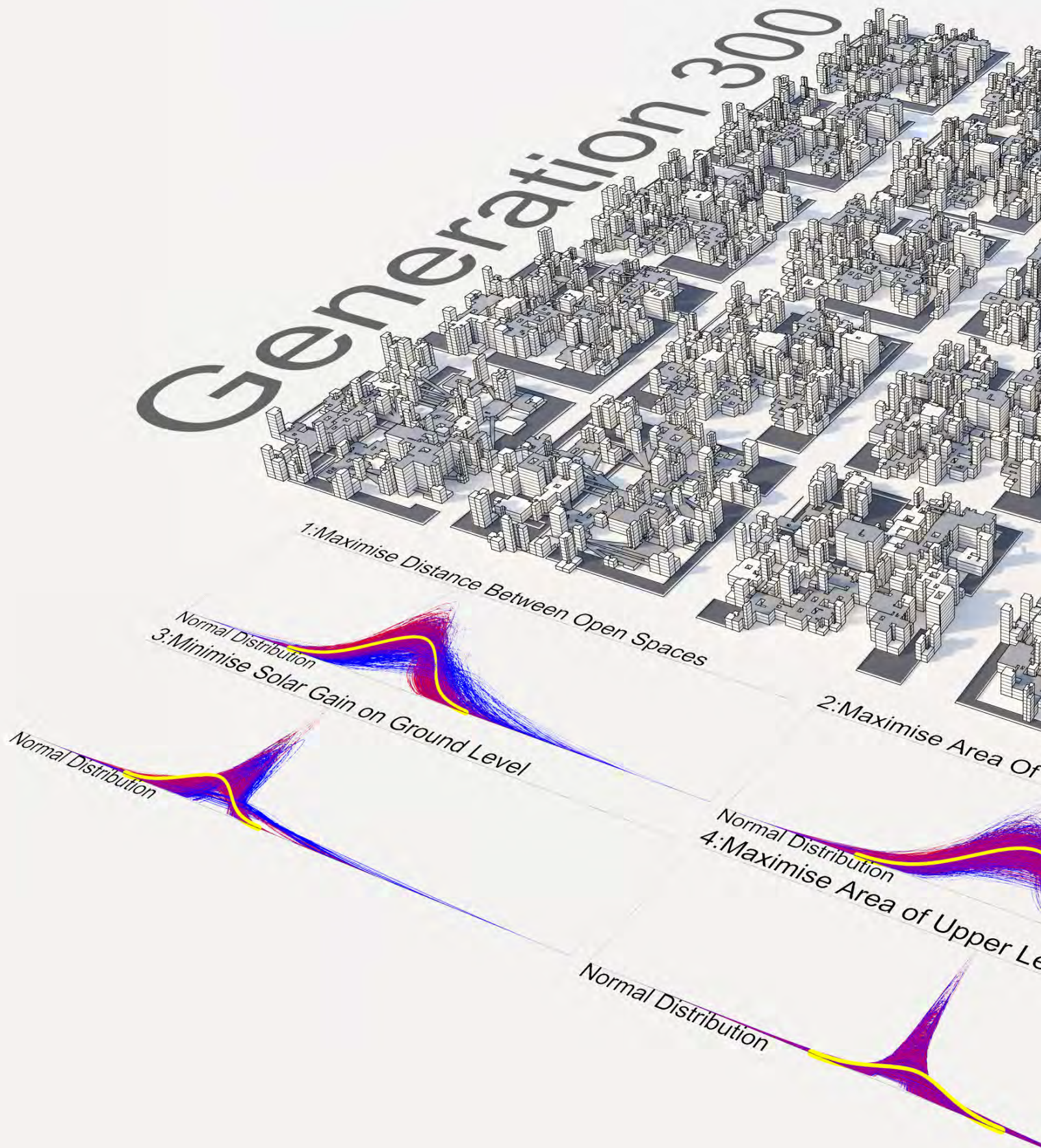
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analysis of generation 200.



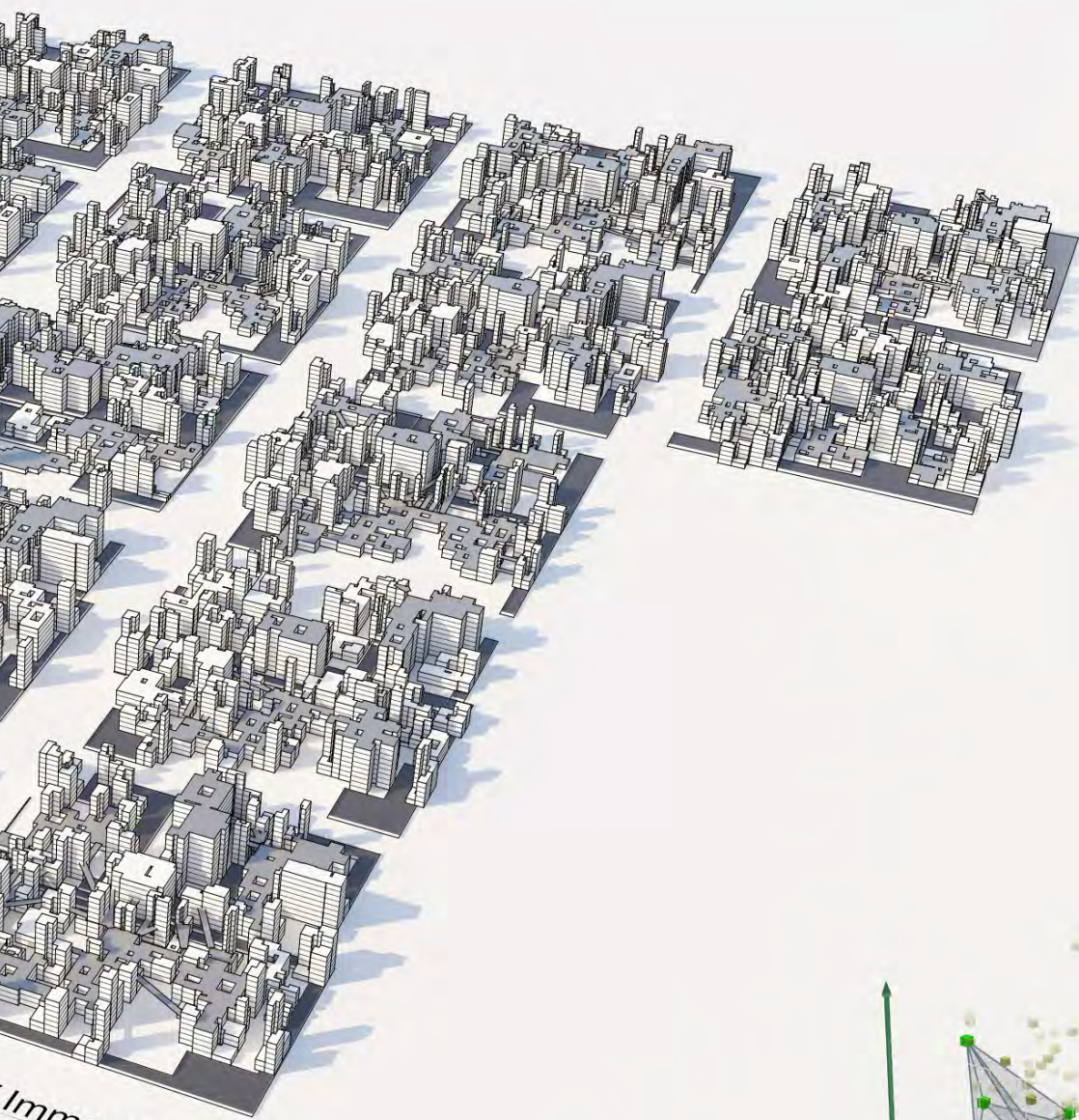
Immediate Open Spaces

Level Spaces



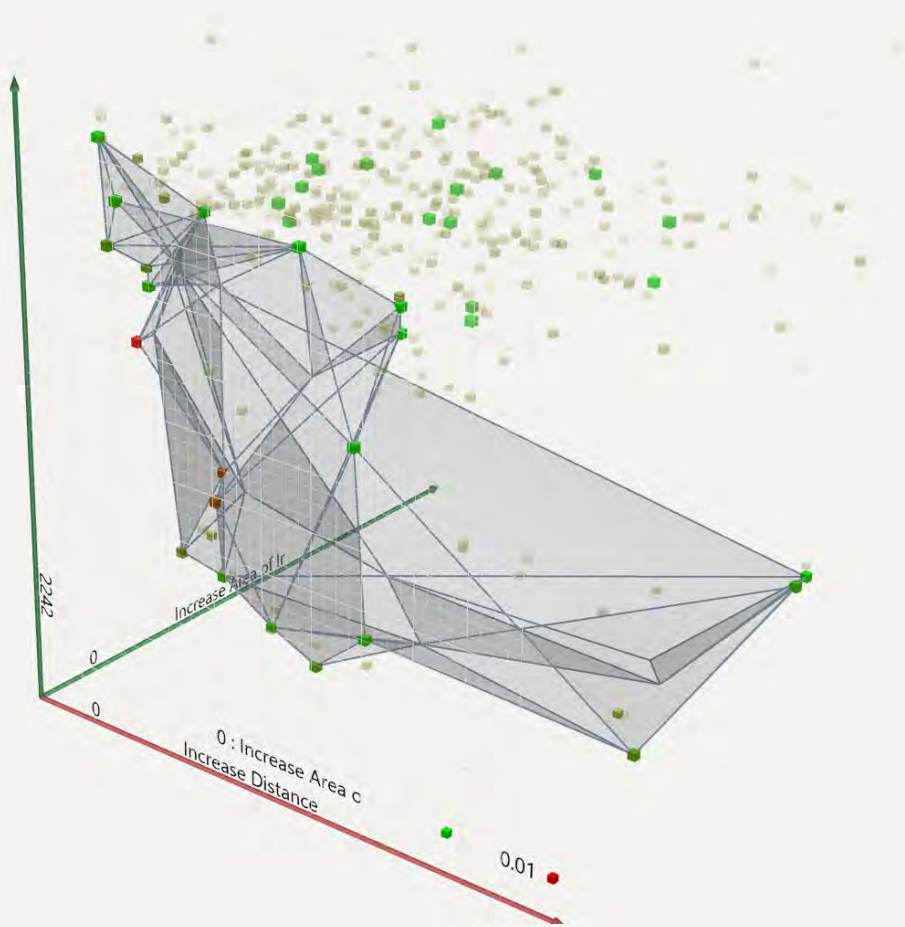


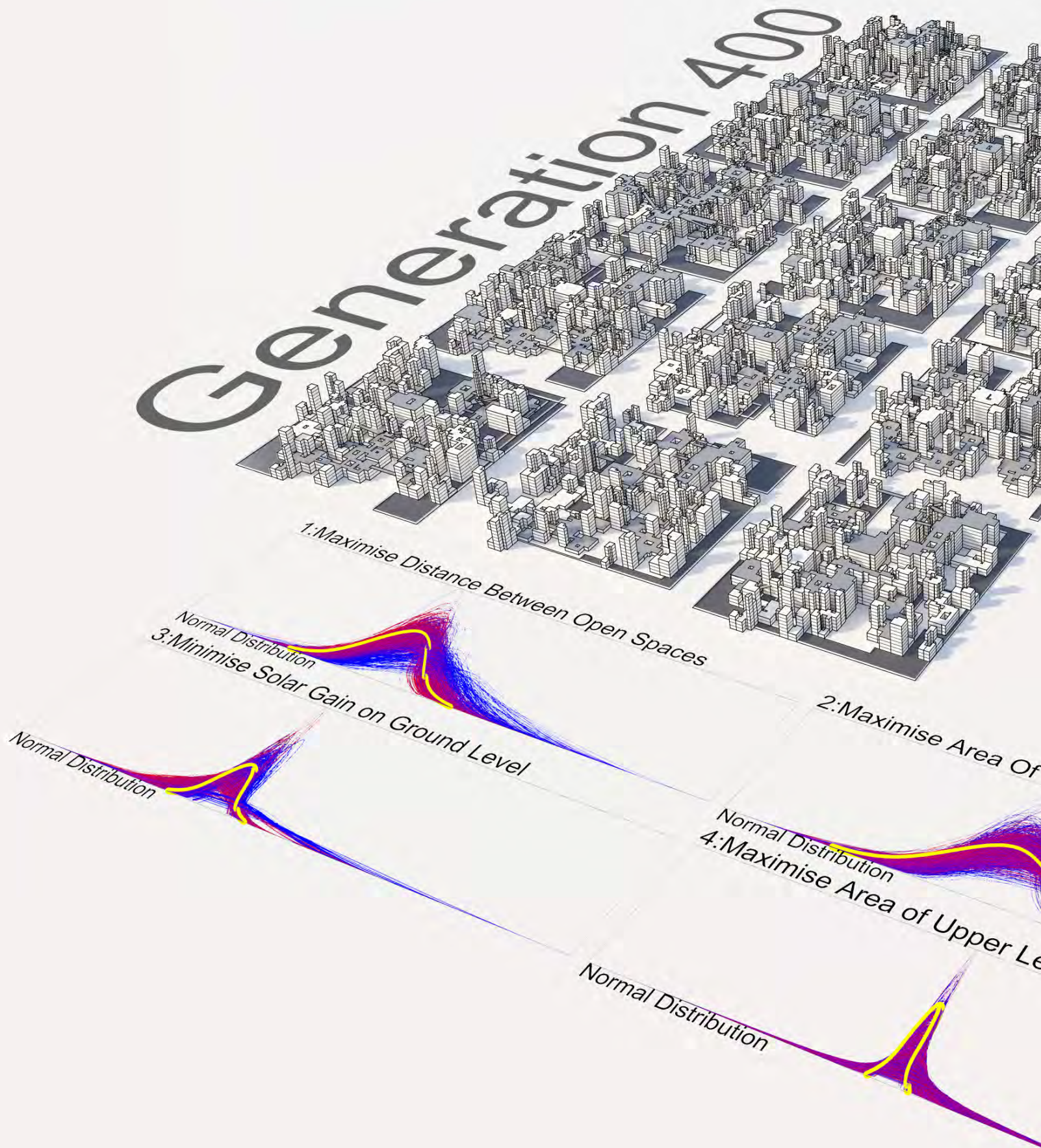
5.22.
Phenotypes and graphical
analysis of generation 300.



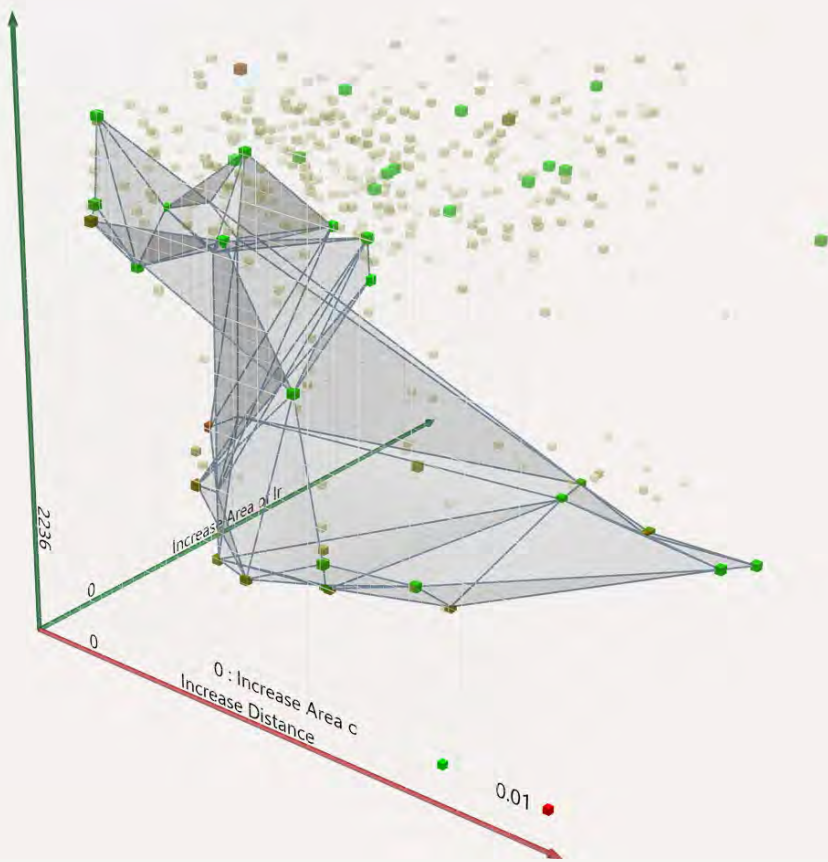
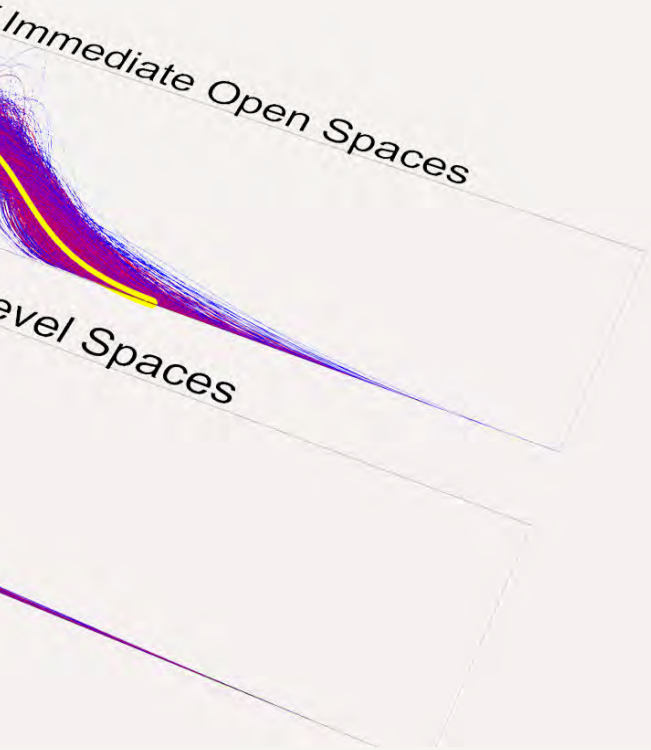
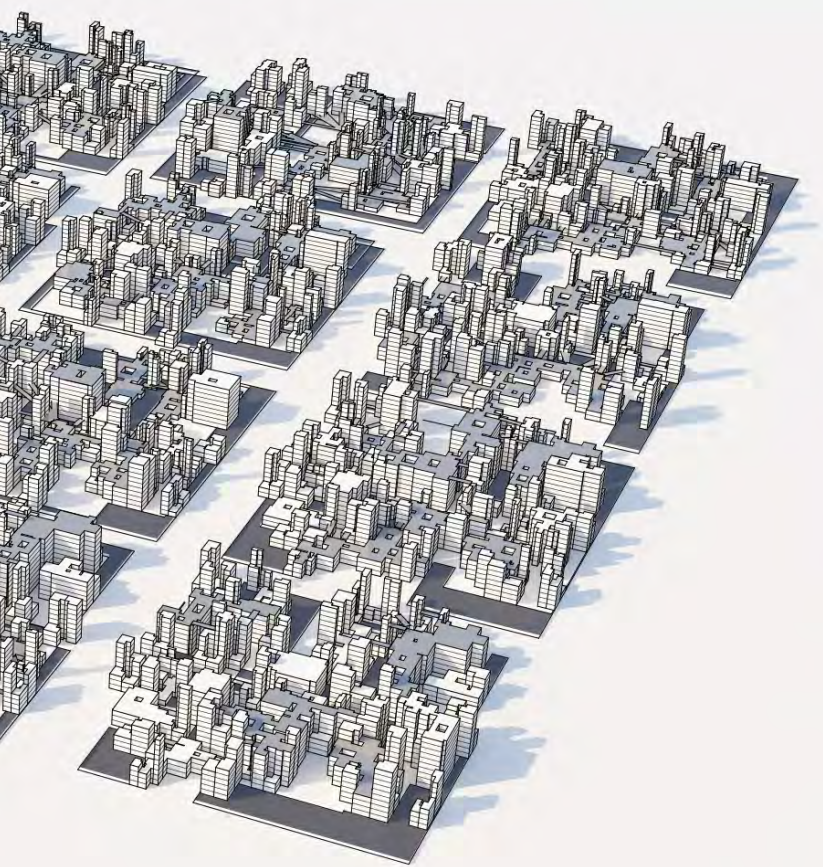
Immediate Open Spaces

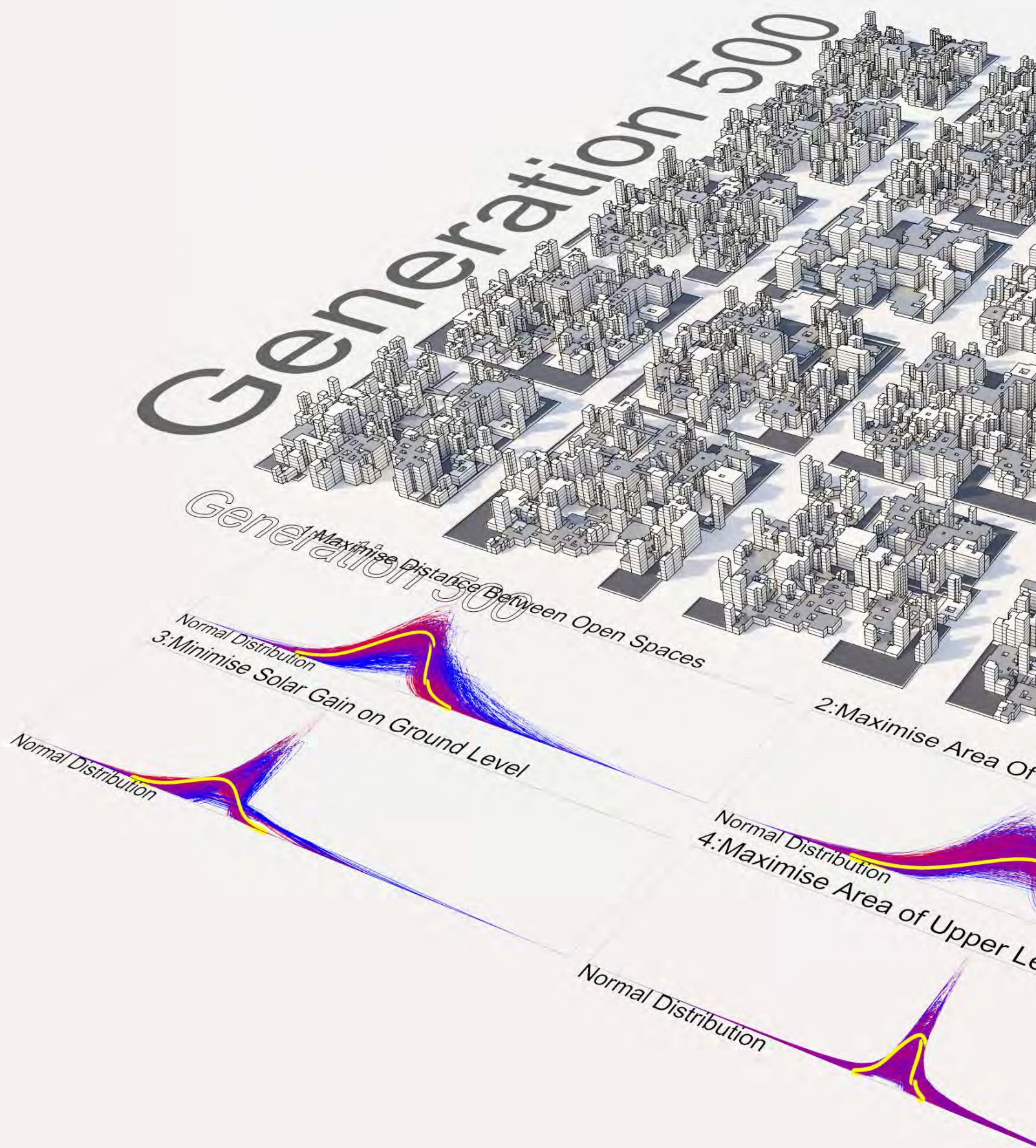
Level Spaces



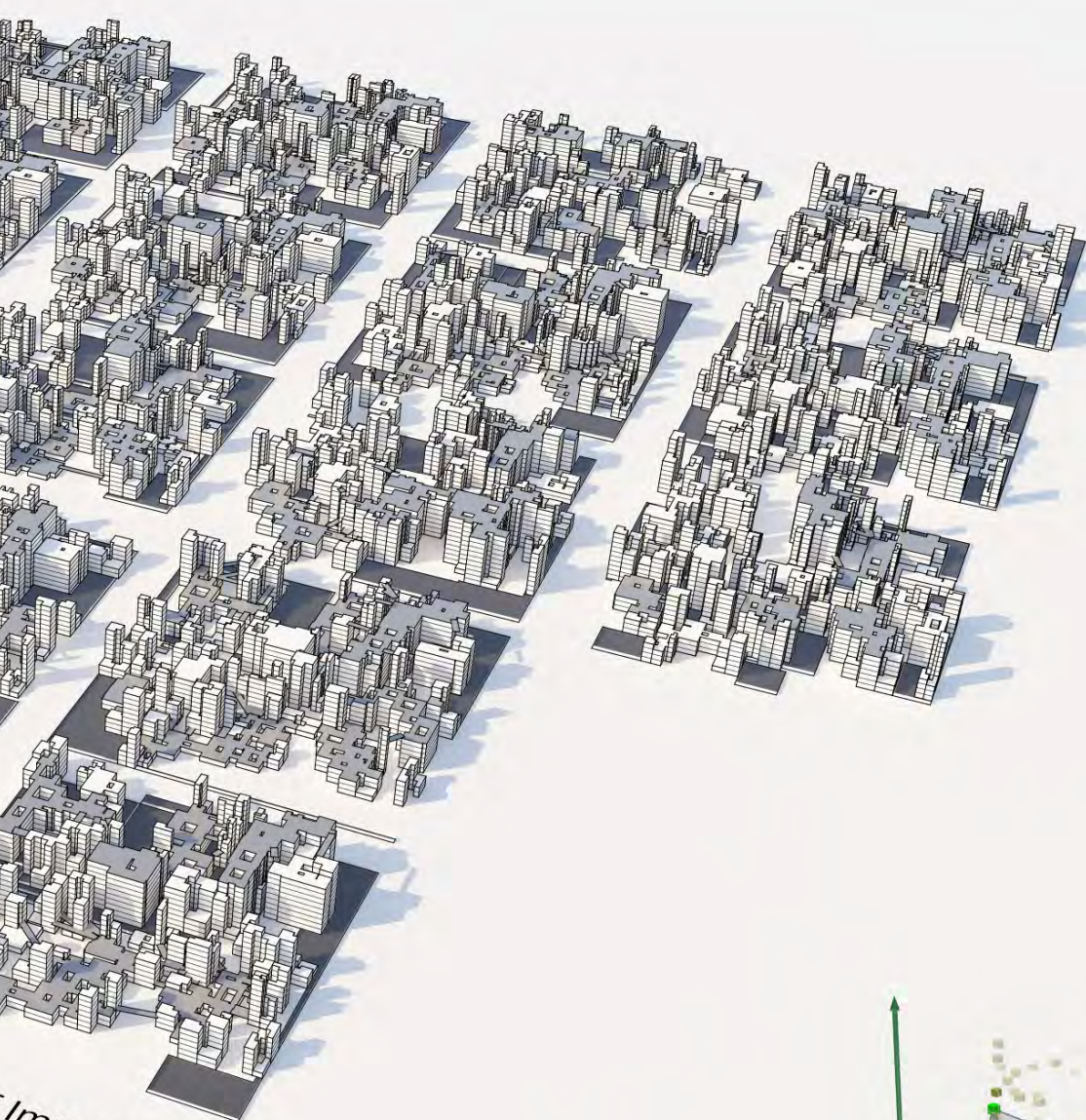


5.23.
Phenotypes and graphical
analysis of generation 400.



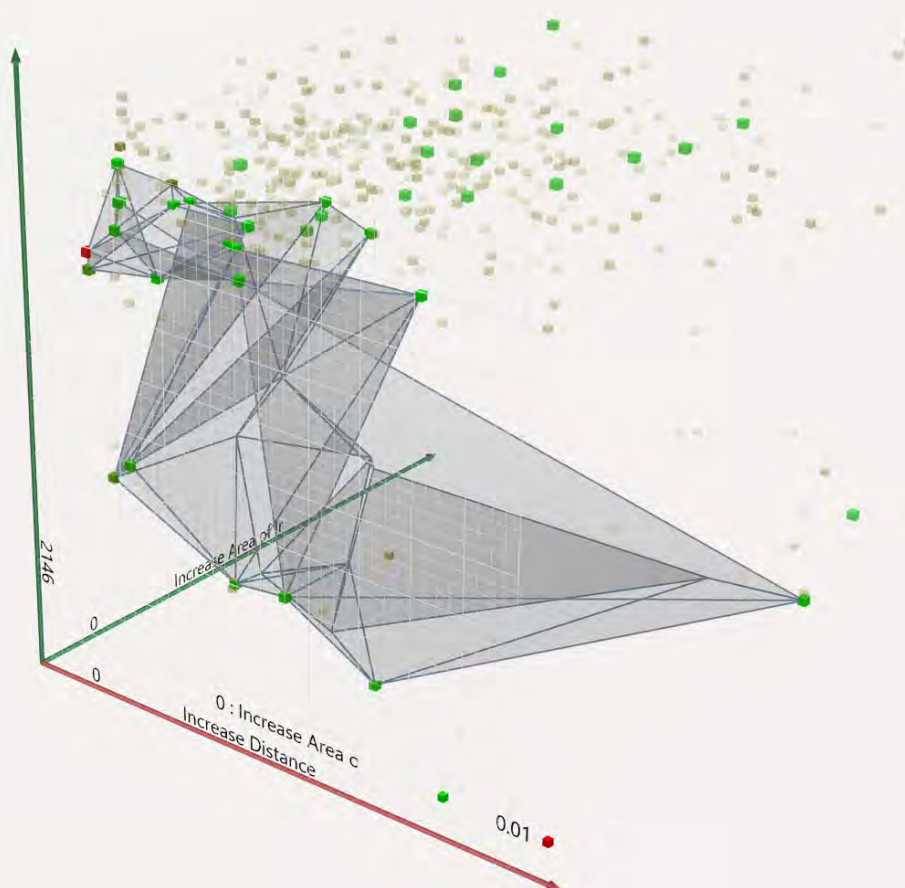


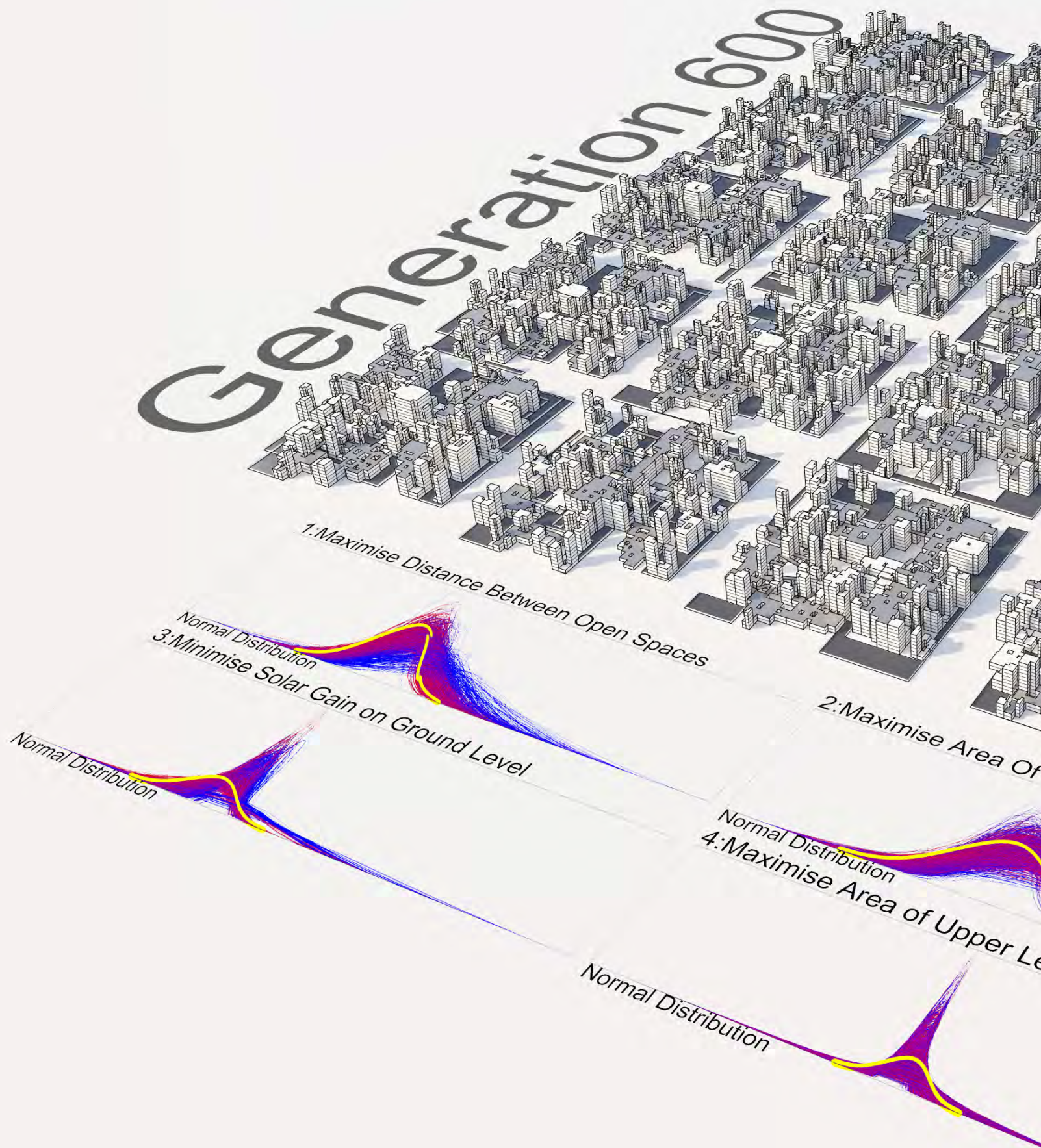
5.24.
Phenotypes and graphical
analysis of generation 500.



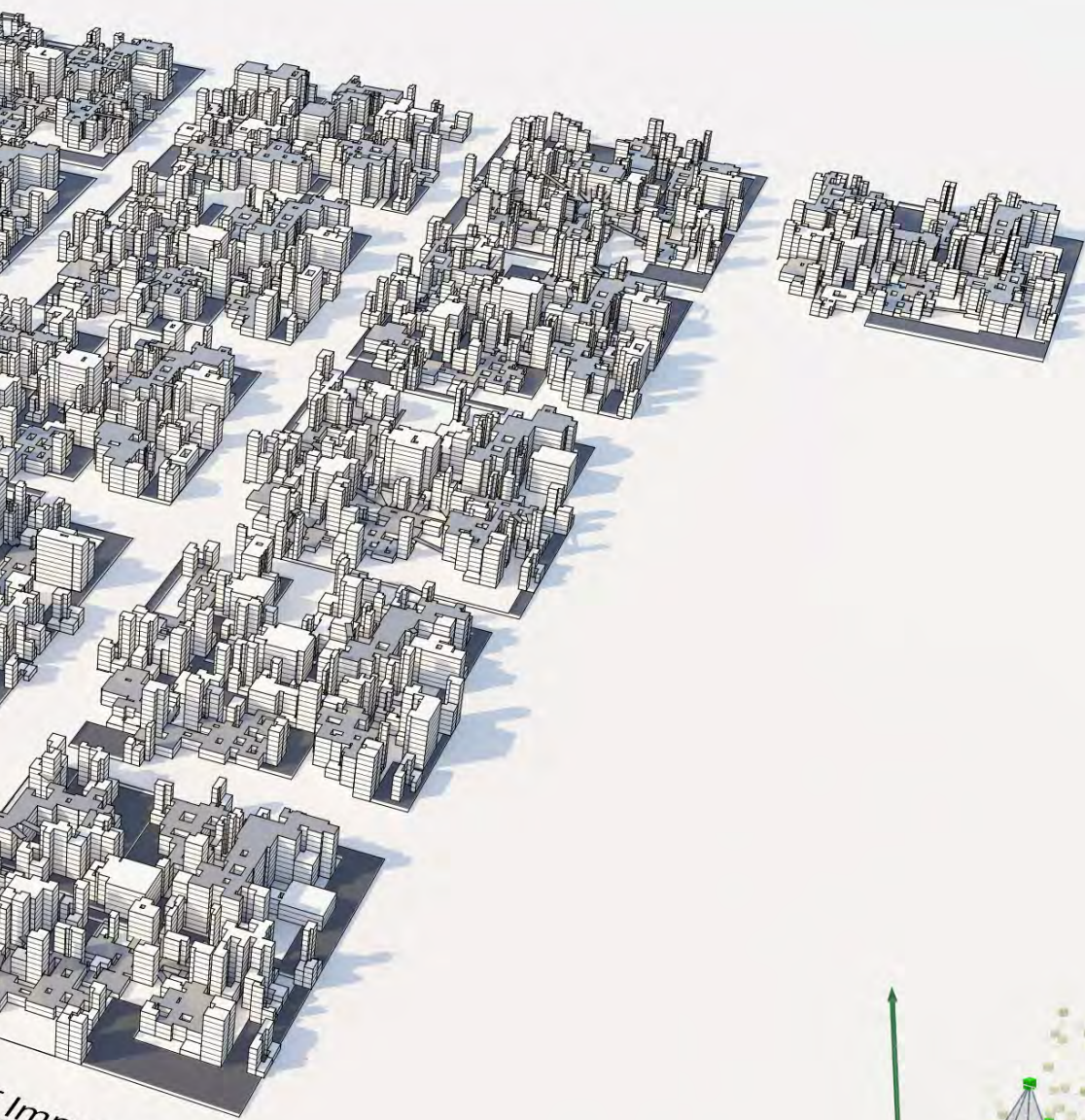
Immediate Open Spaces

Level Spaces



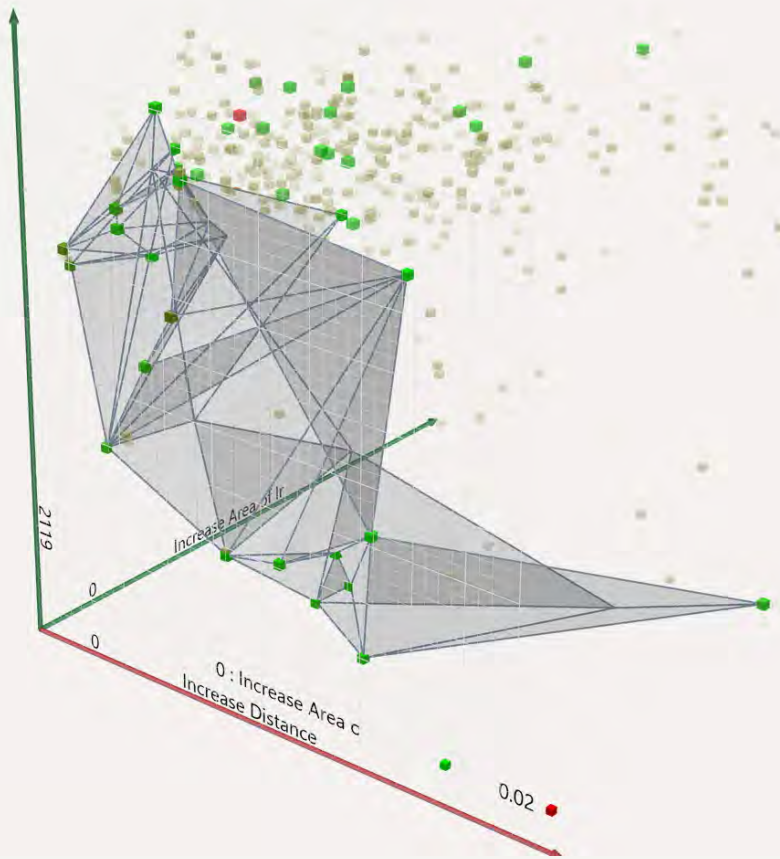


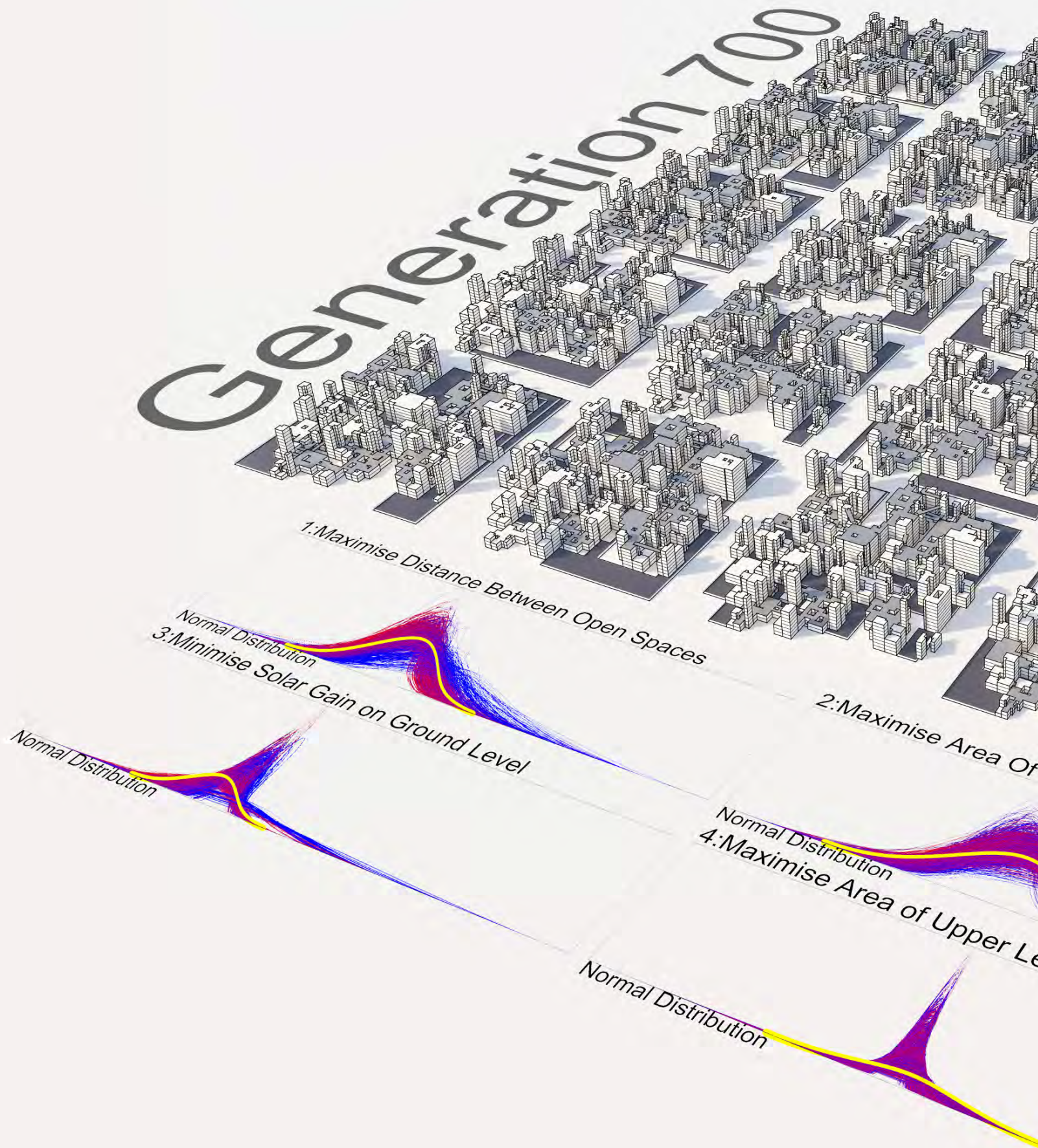
5.25.
Phenotypes and graphical
analysis of generation 600.



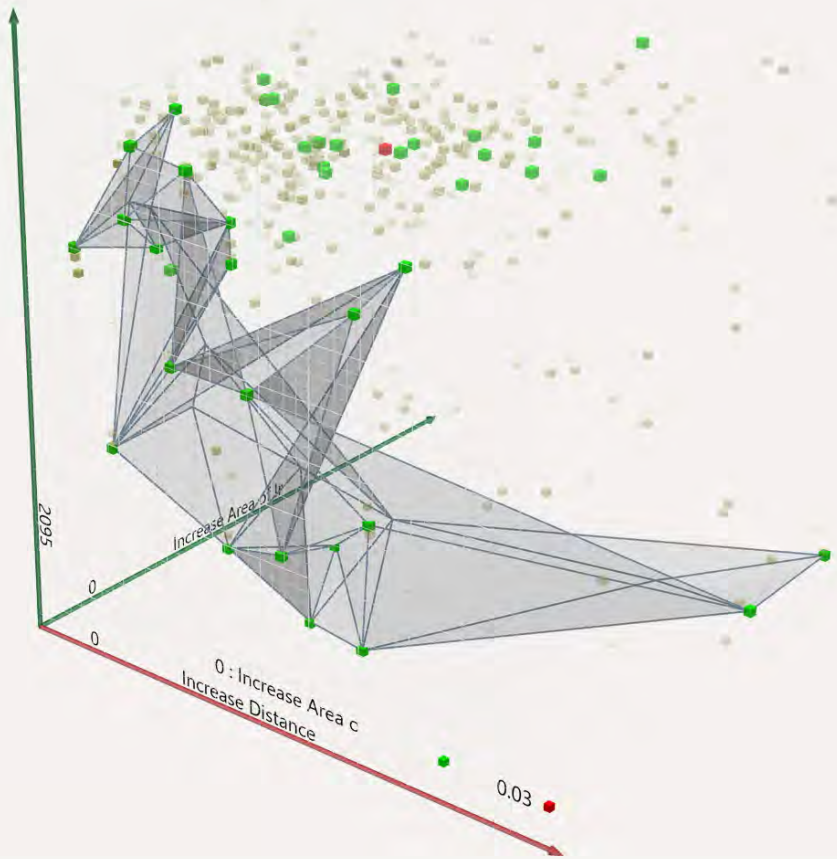
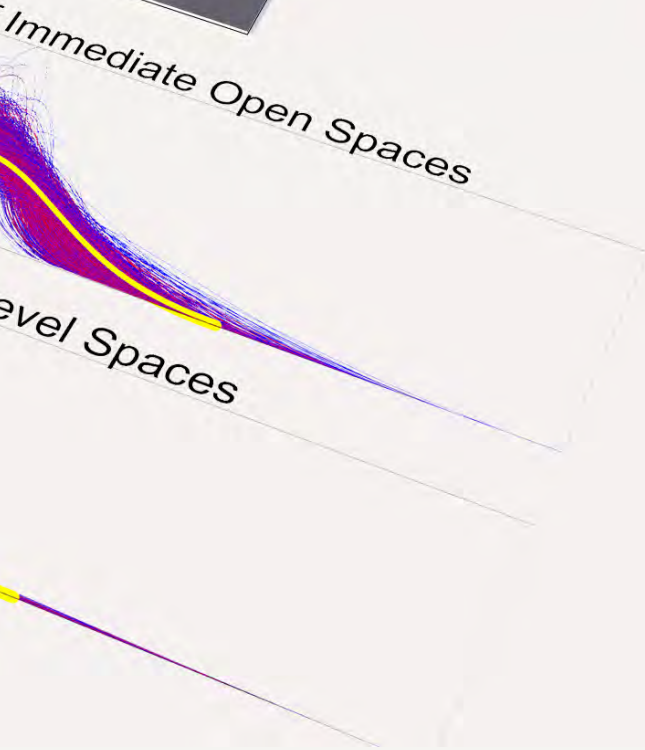
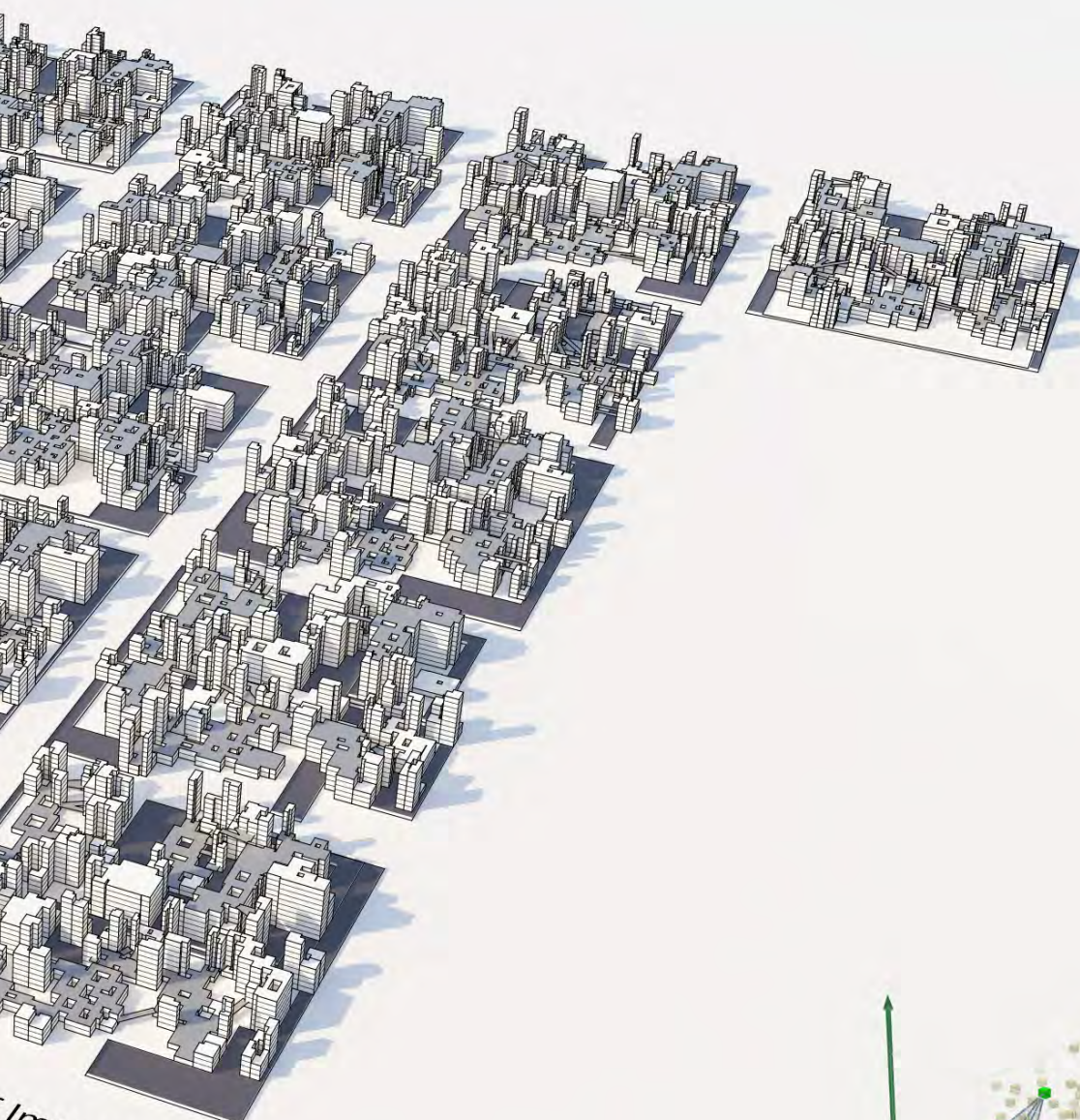
Immediate Open Spaces

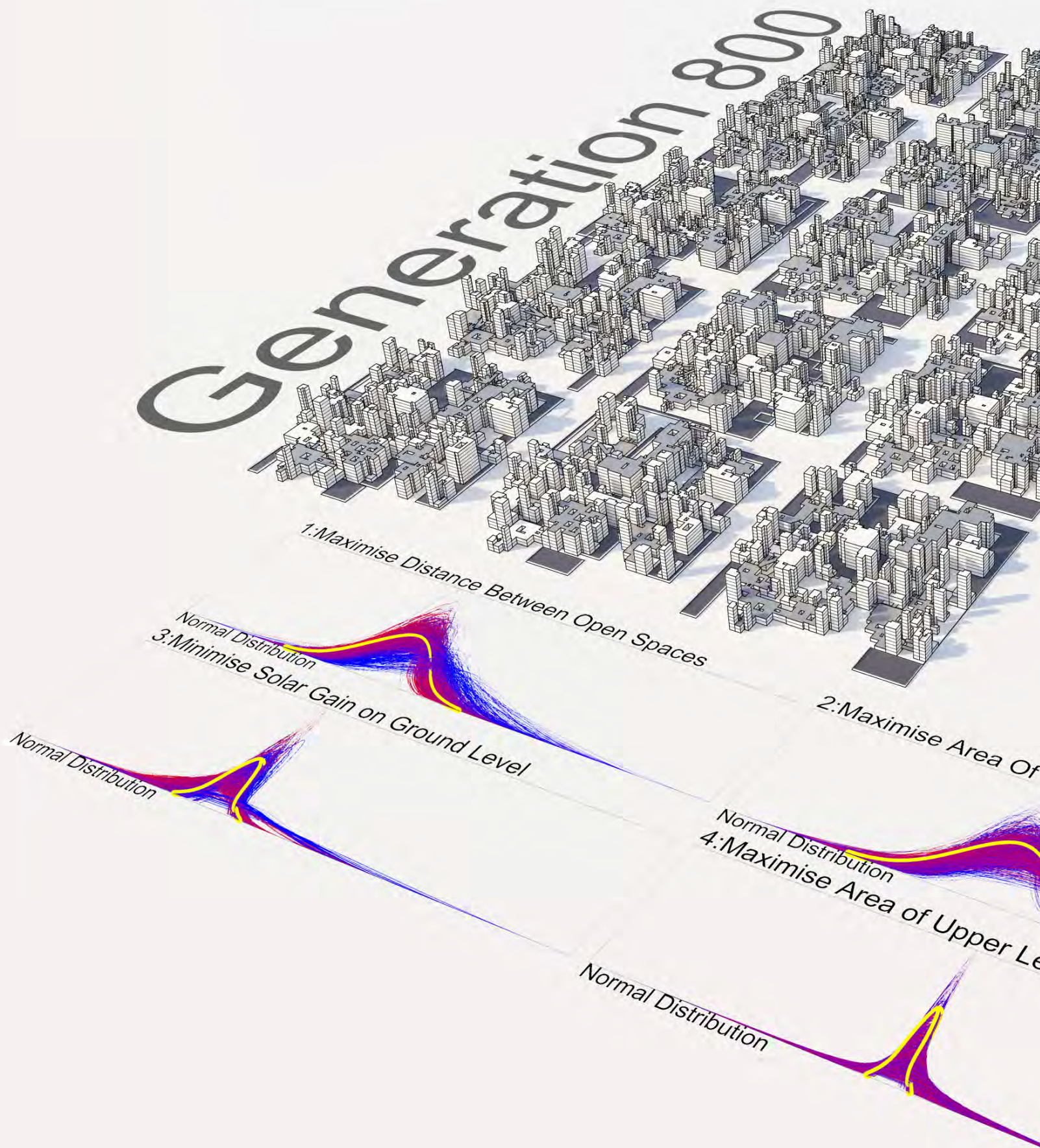
Level Spaces



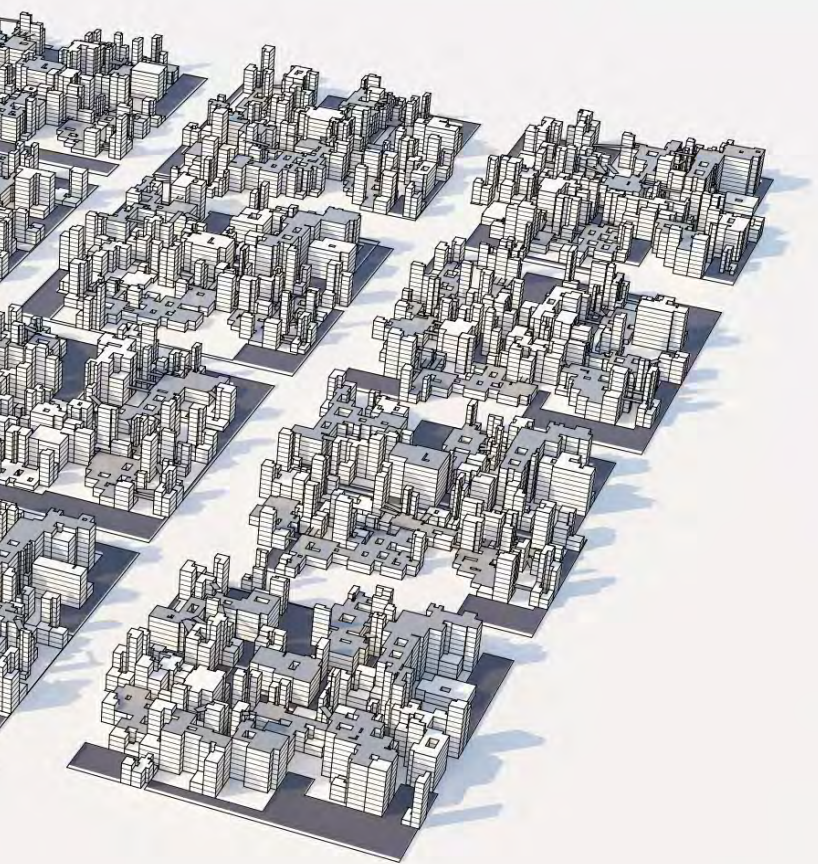


5.26.
Phenotypes and graphical
analysis of generation 700.



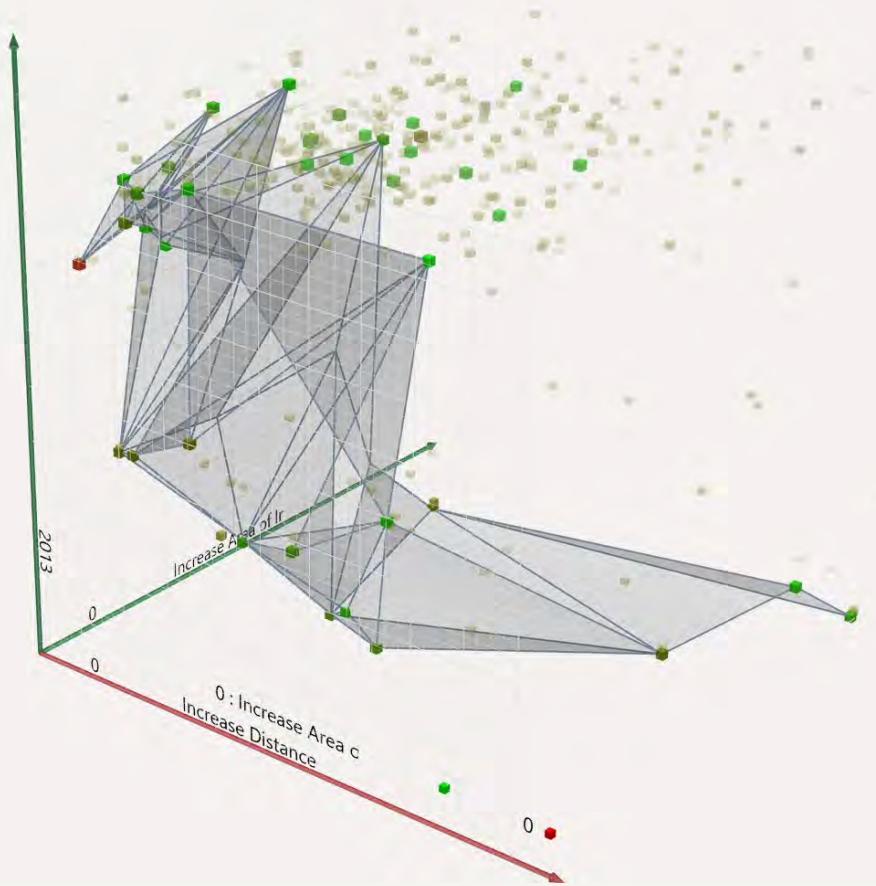


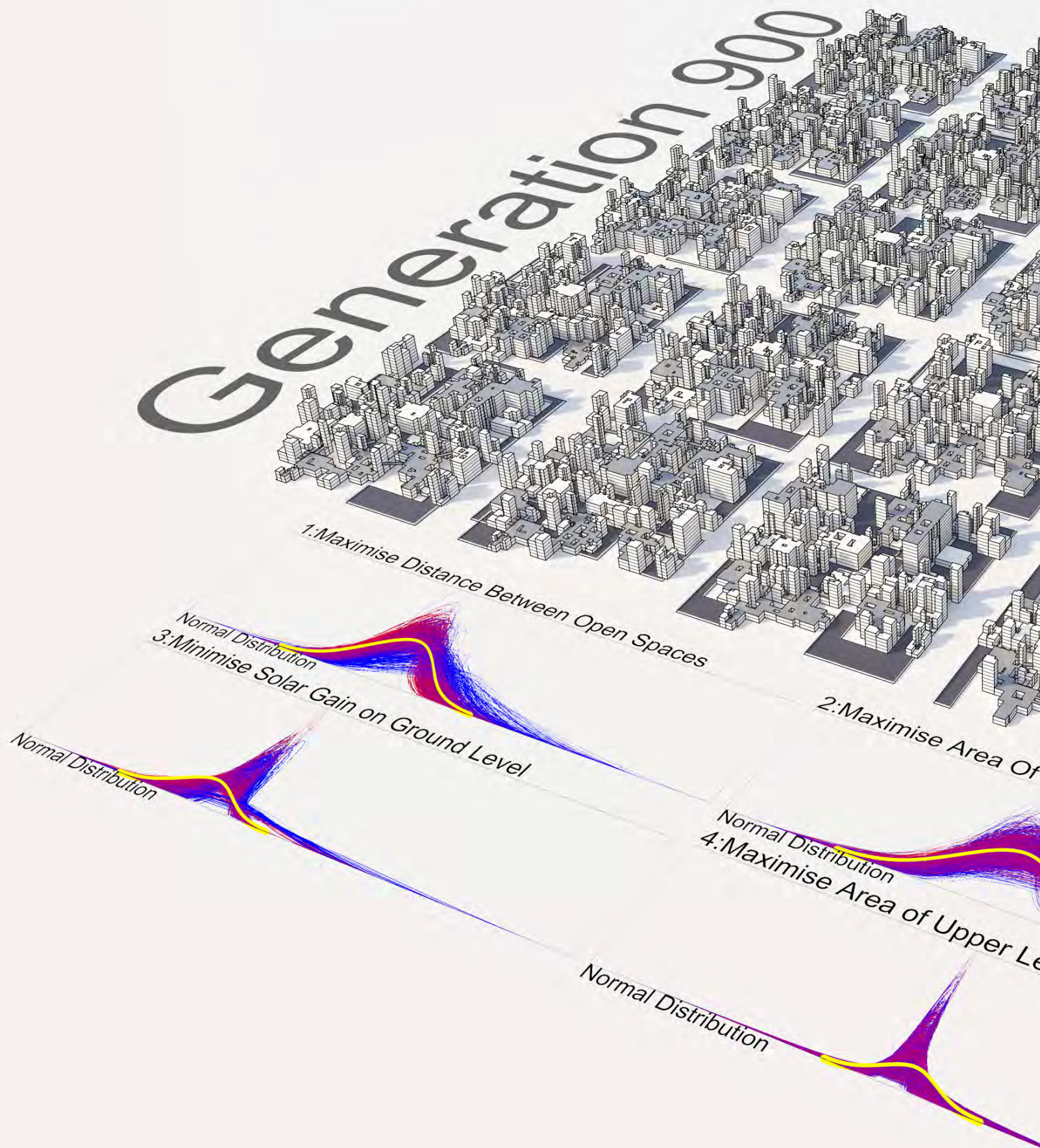
5.27.
Phenotypes and graphical
analysis of generation 800.



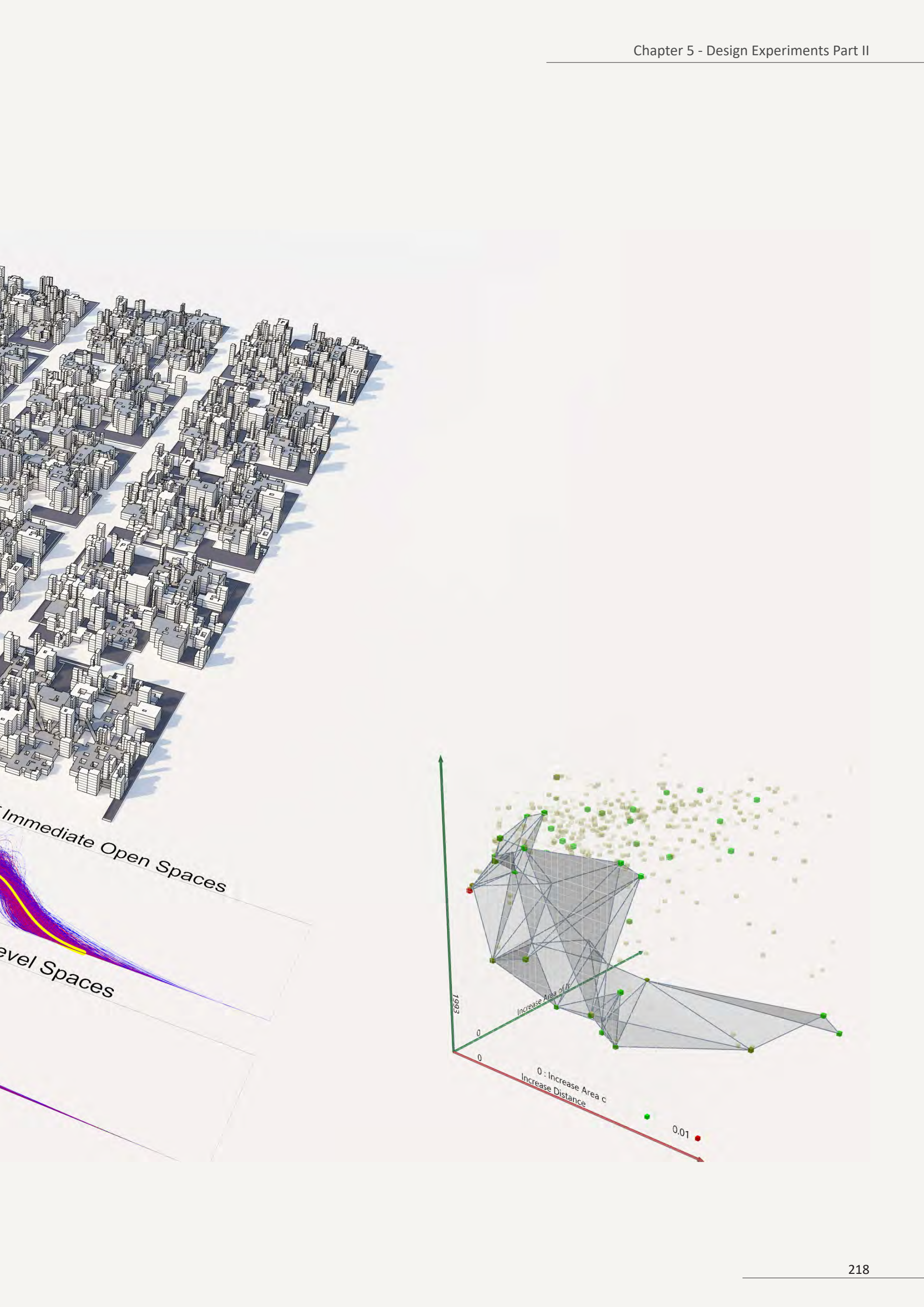
Immediate Open Spaces

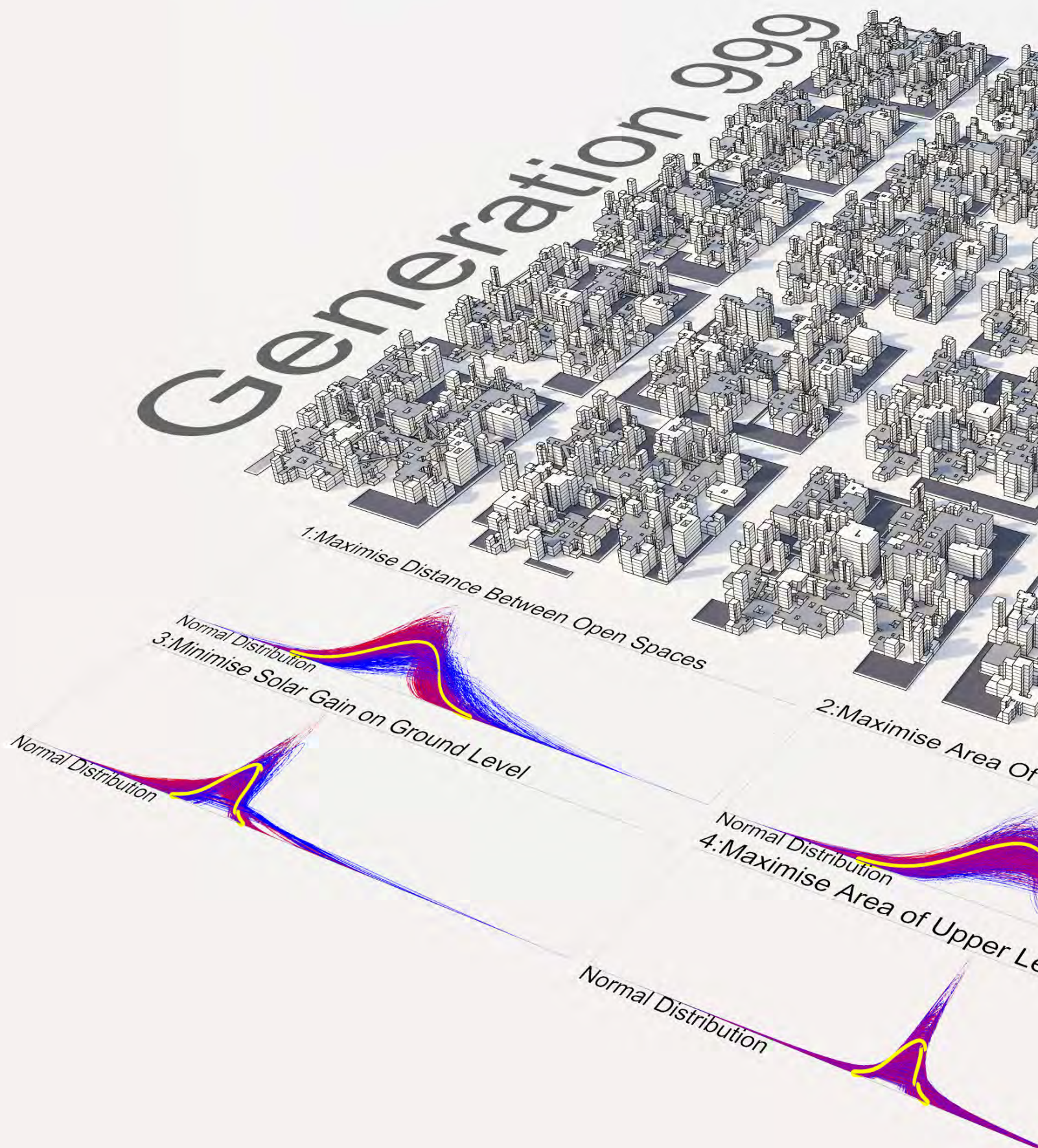
Level Spaces



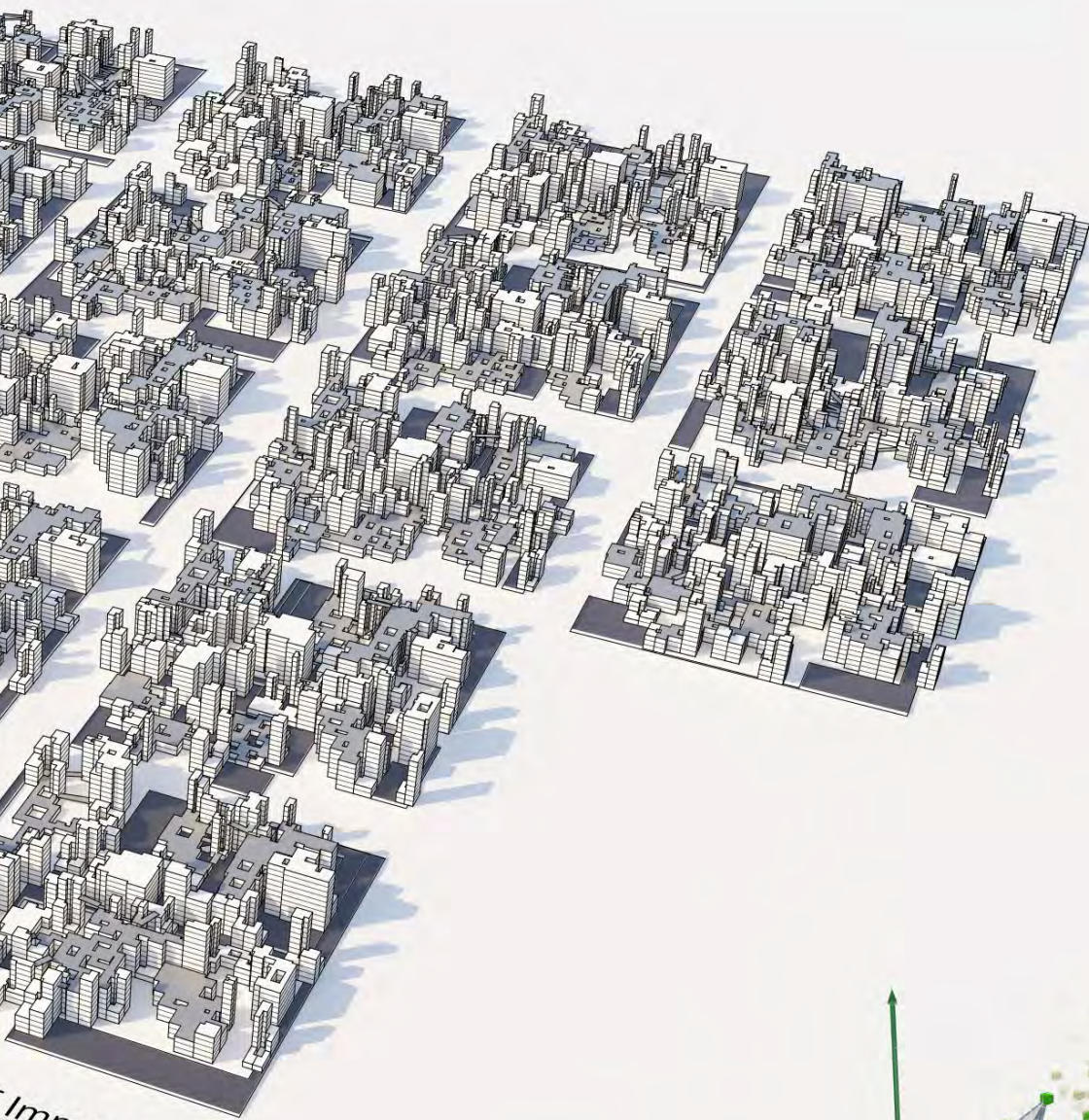


5.28.
Phenotypes and graphical
analysis of generation 900.



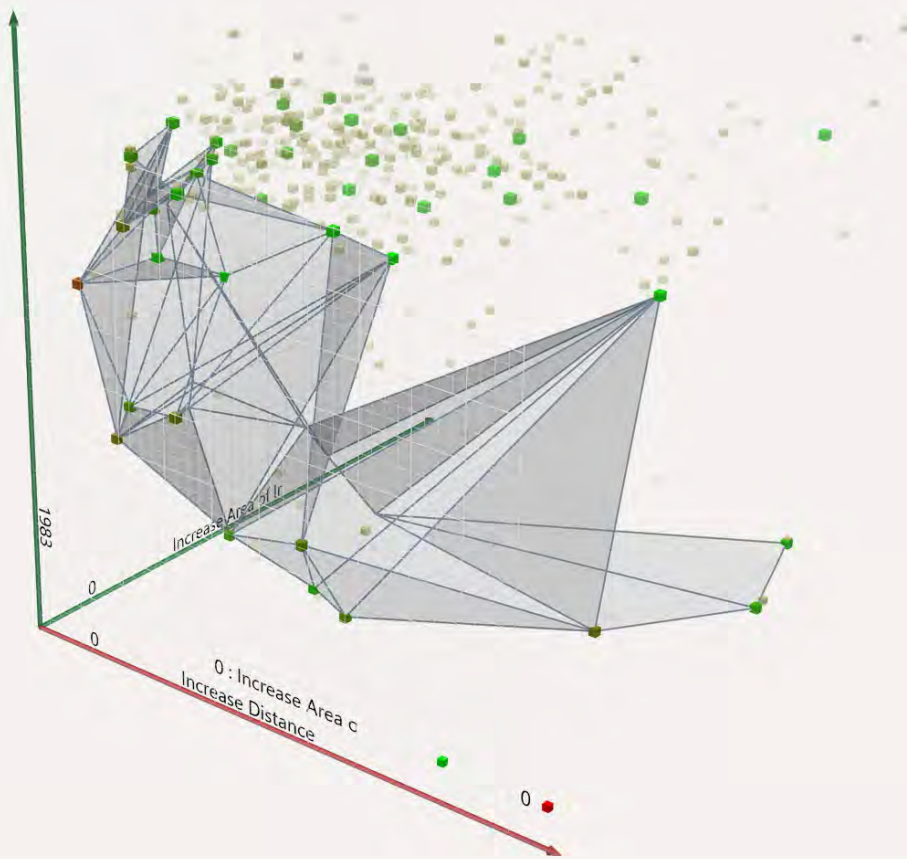


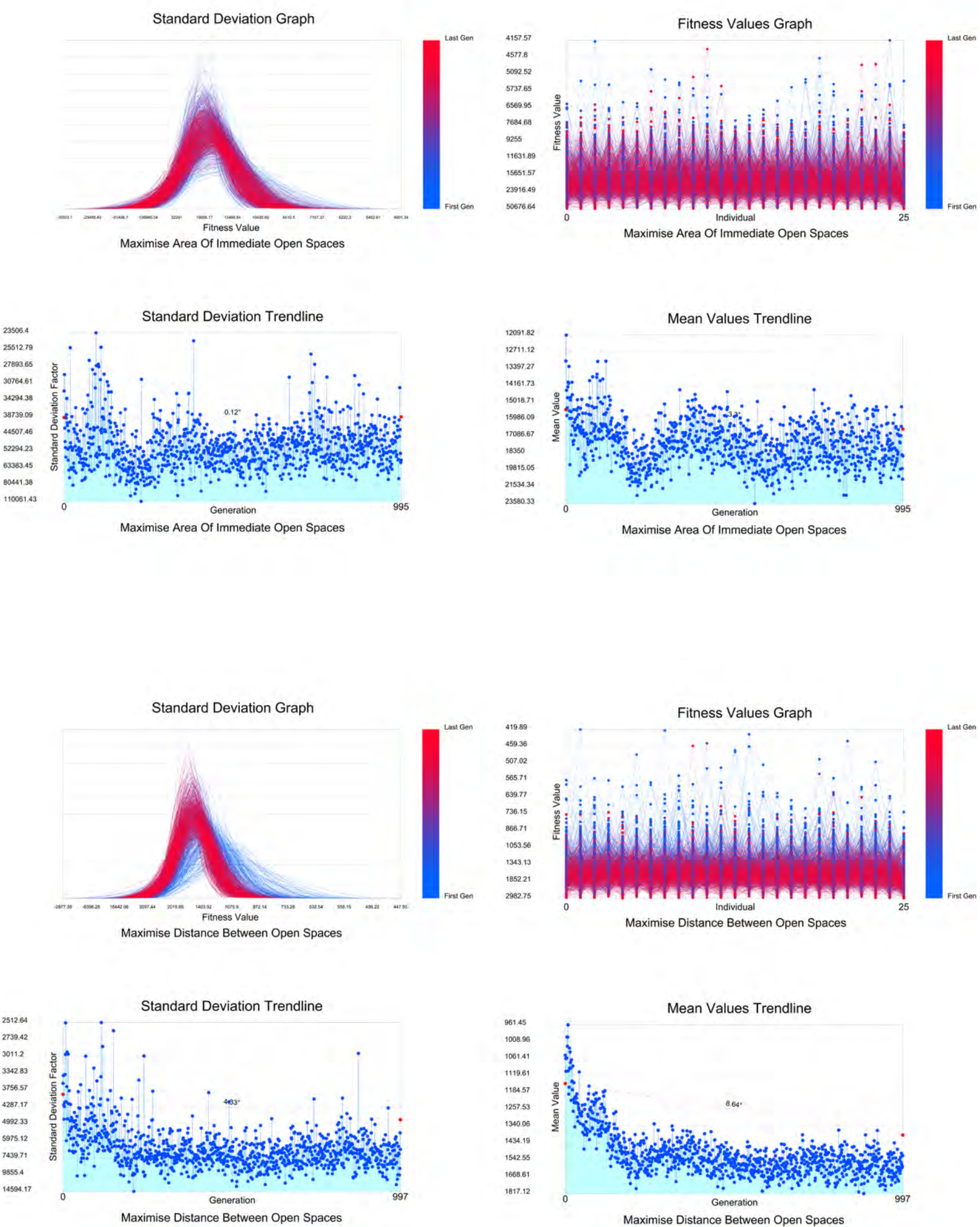
5.29.
Phenotypes and graphical
analysis of generation 999.



Immediate Open Spaces

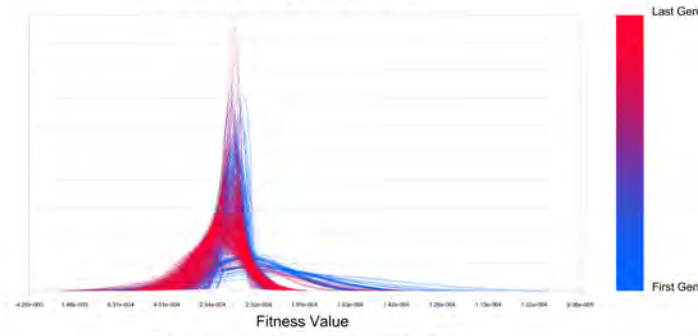
Level Spaces





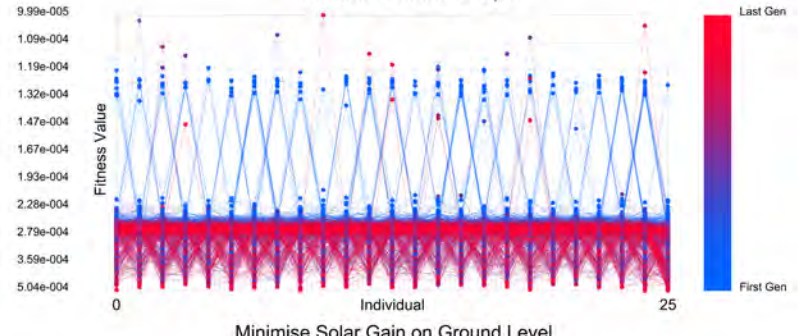
5.30.
Statistical analysis of the
simulation's output

Standard Deviation Graph



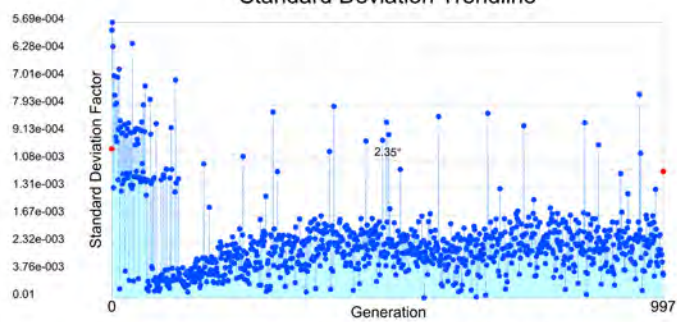
Minimise Solar Gain on Ground Level

Fitness Values Graph



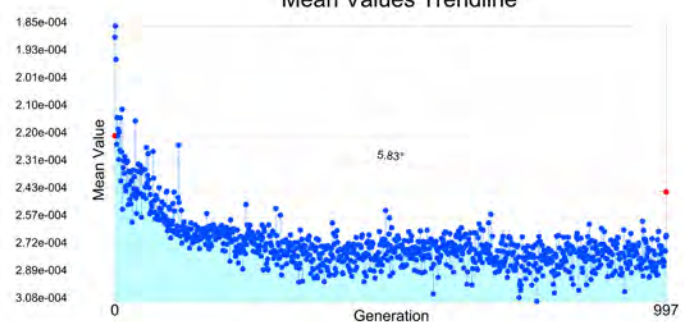
Minimise Solar Gain on Ground Level

Standard Deviation Trendline



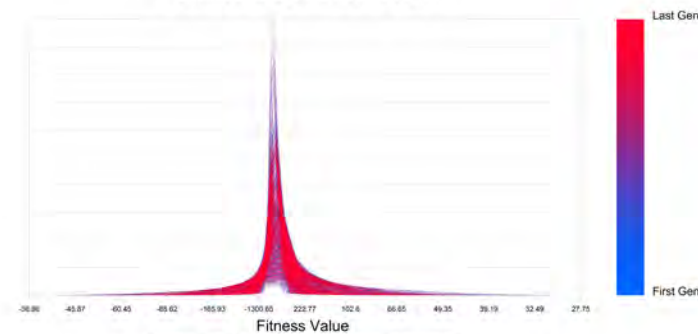
Minimise Solar Gain on Ground Level

Mean Values Trendline



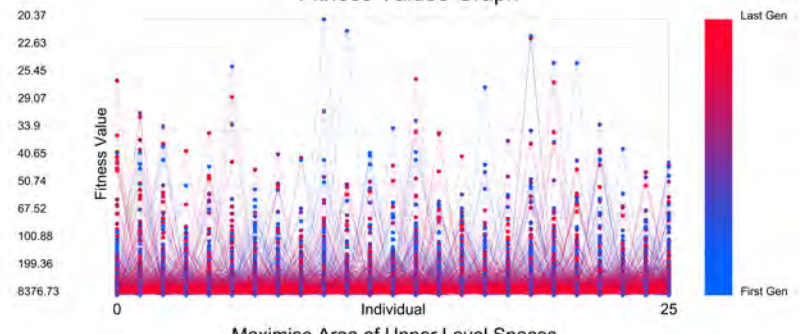
Minimise Solar Gain on Ground Level

Standard Deviation Graph



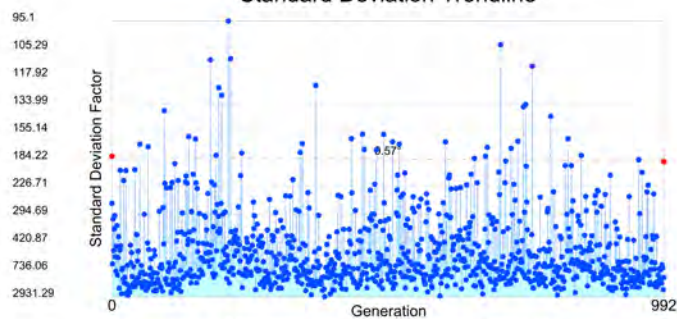
Maximise Area of Upper Level Spaces

Fitness Values Graph



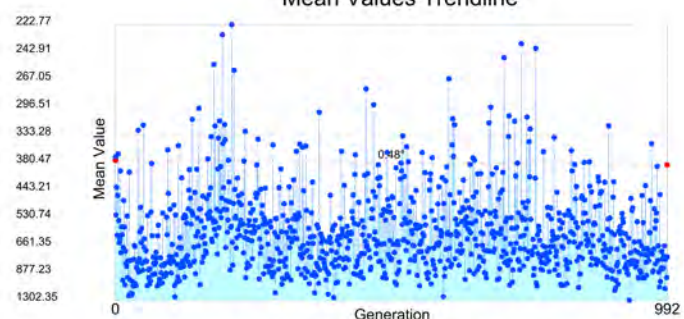
Maximise Area of Upper Level Spaces

Standard Deviation Trendline

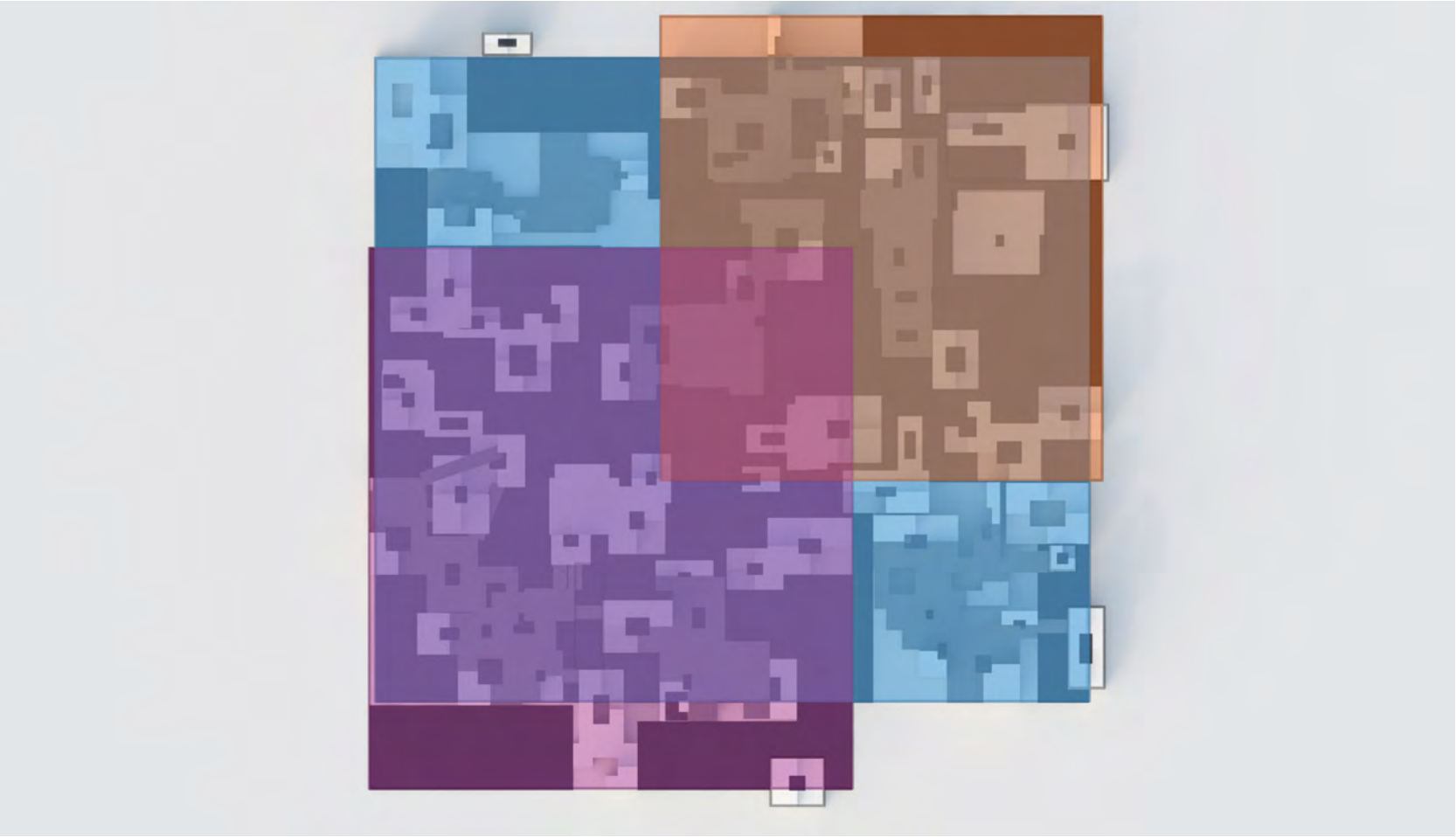
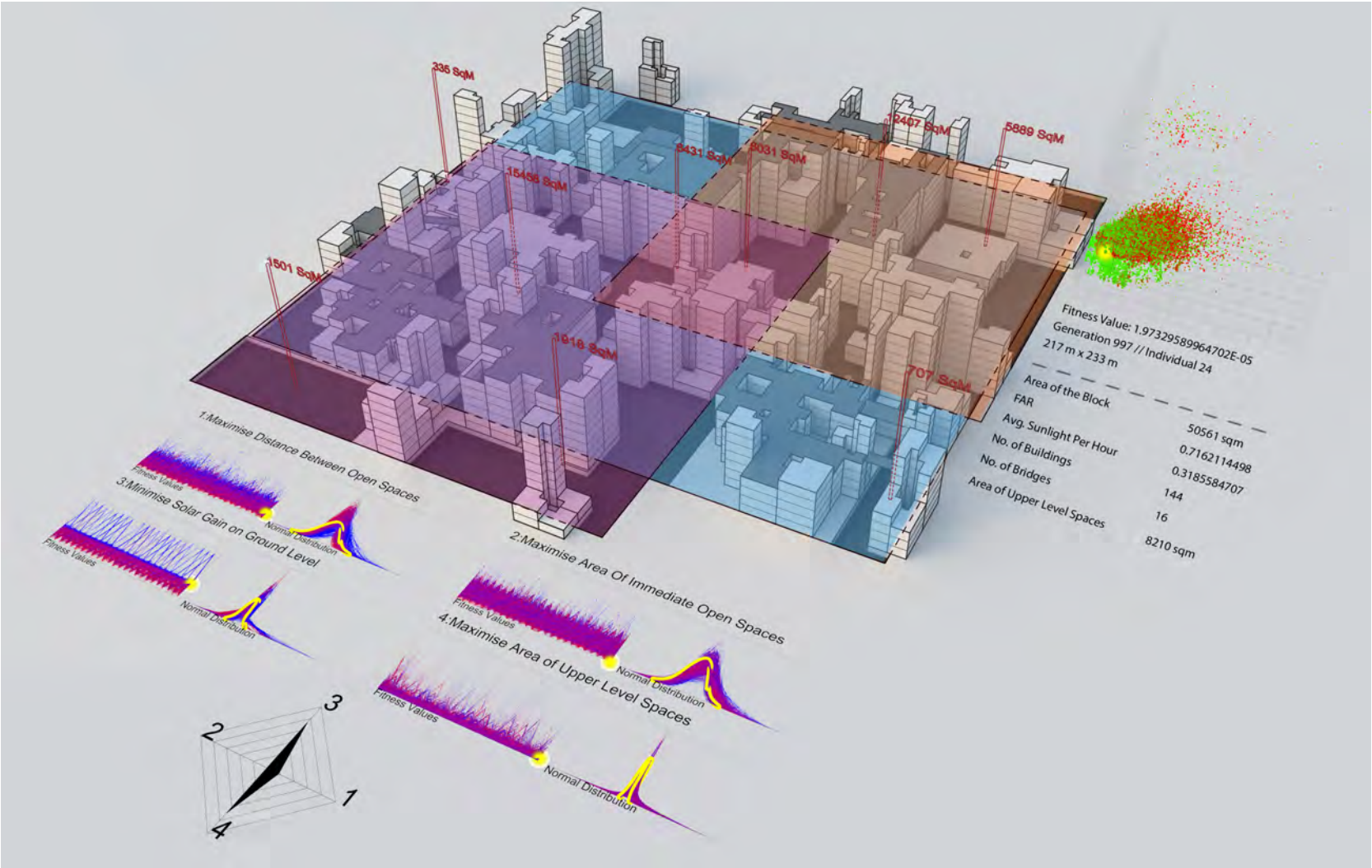


Maximise Area of Upper Level Spaces

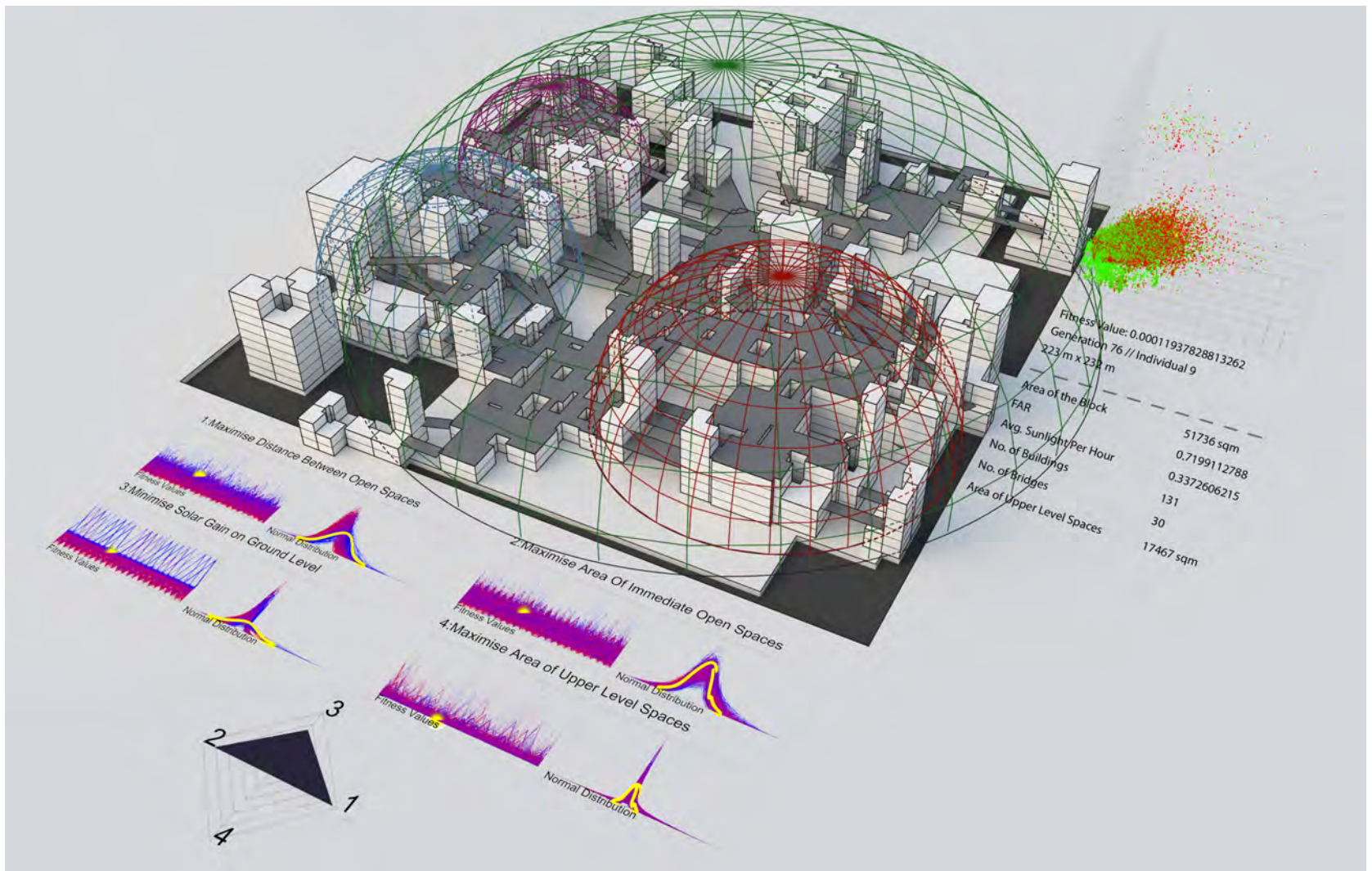
Mean Values Trendline



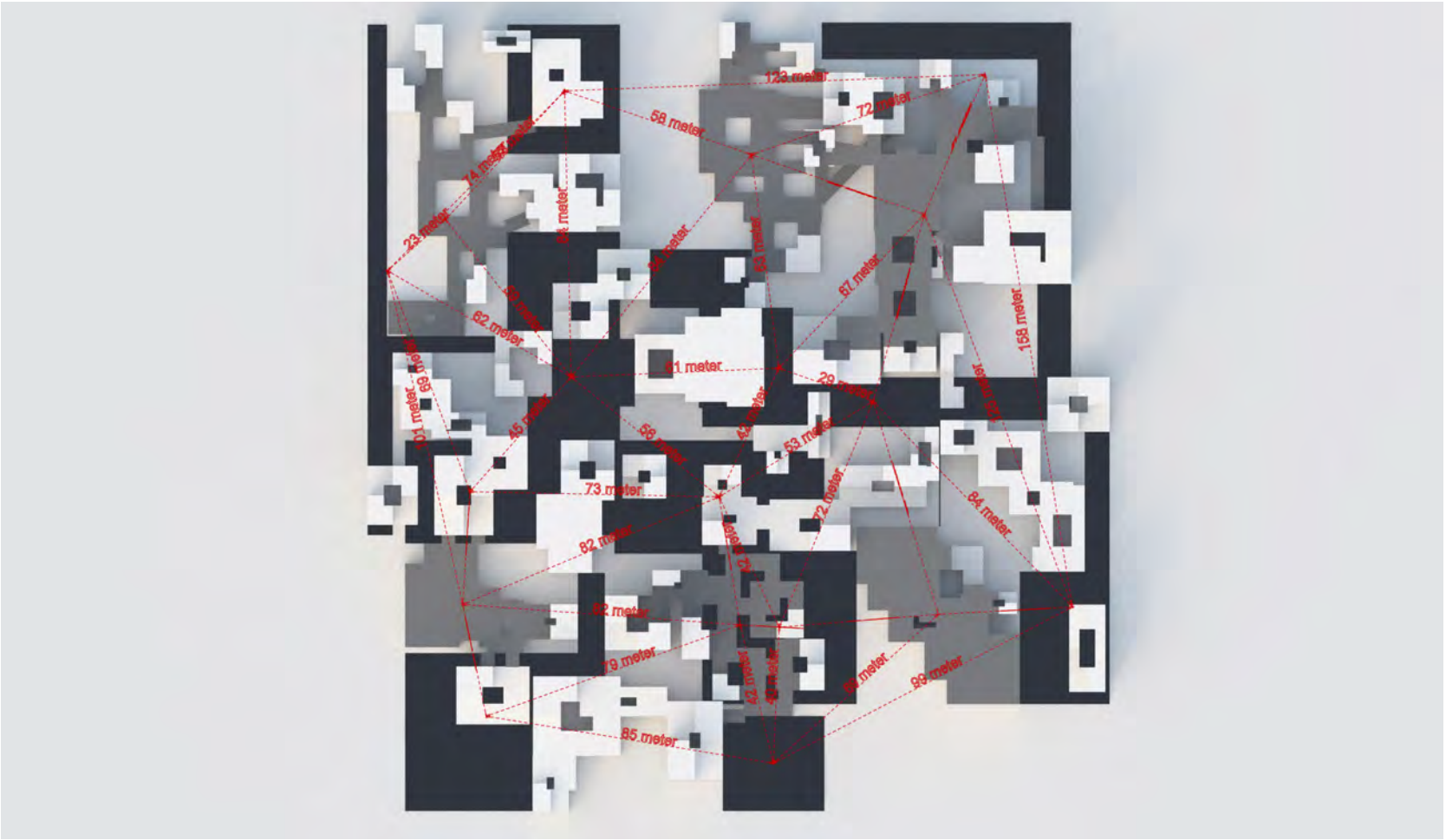
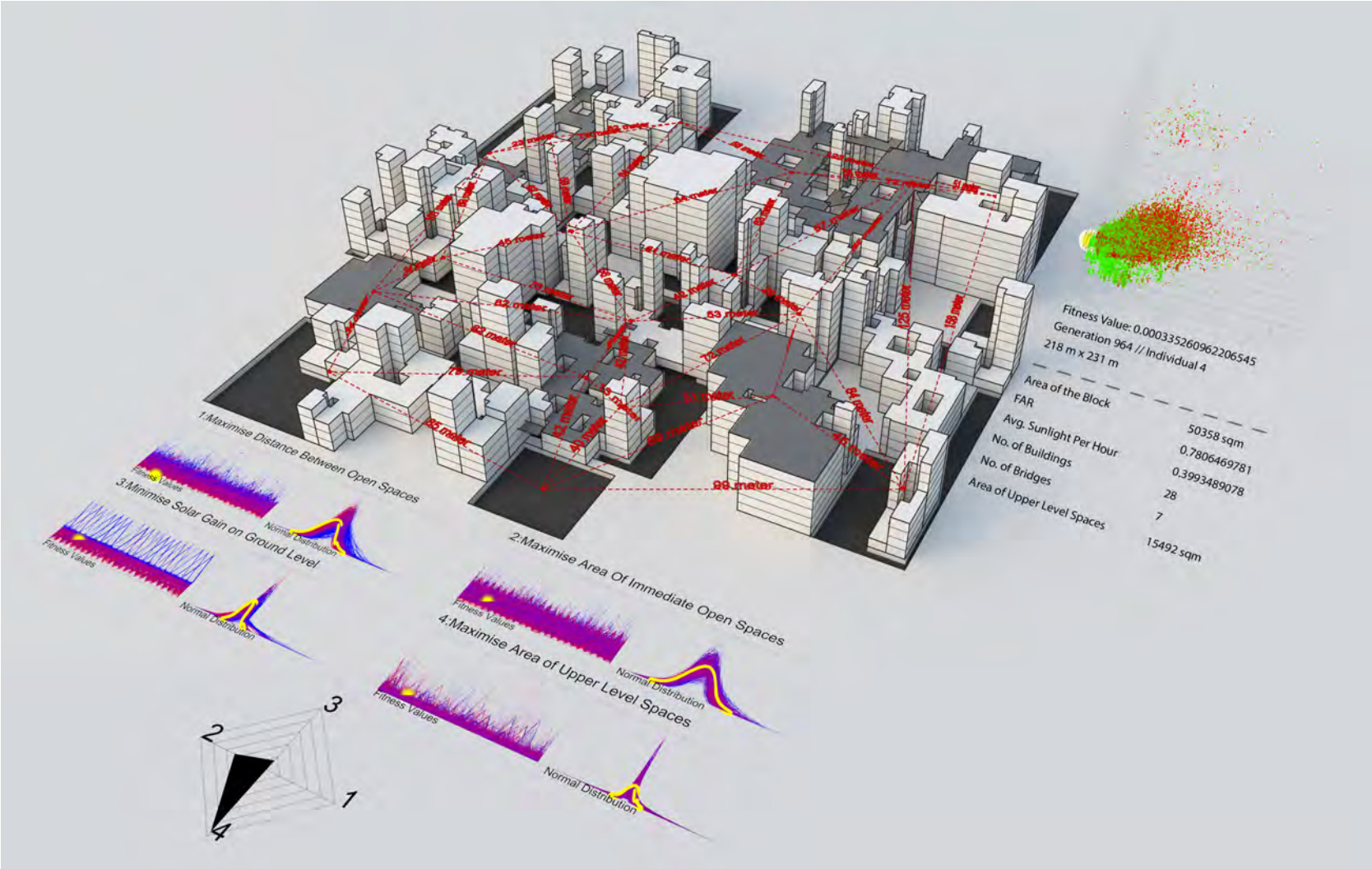
Maximise Area of Upper Level Spaces



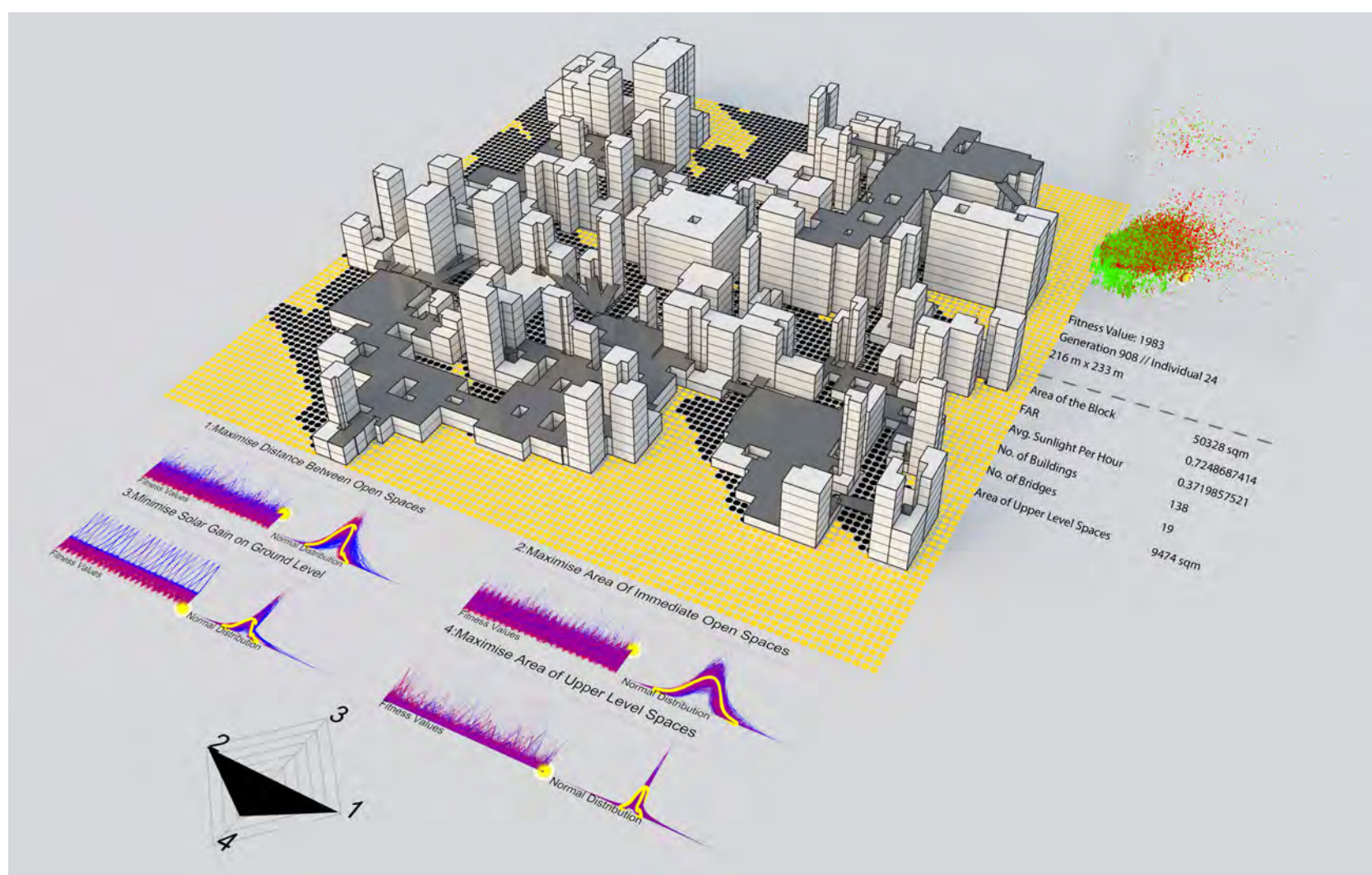
5.31. Fittest solution for Neighbourhood Spaces objective.



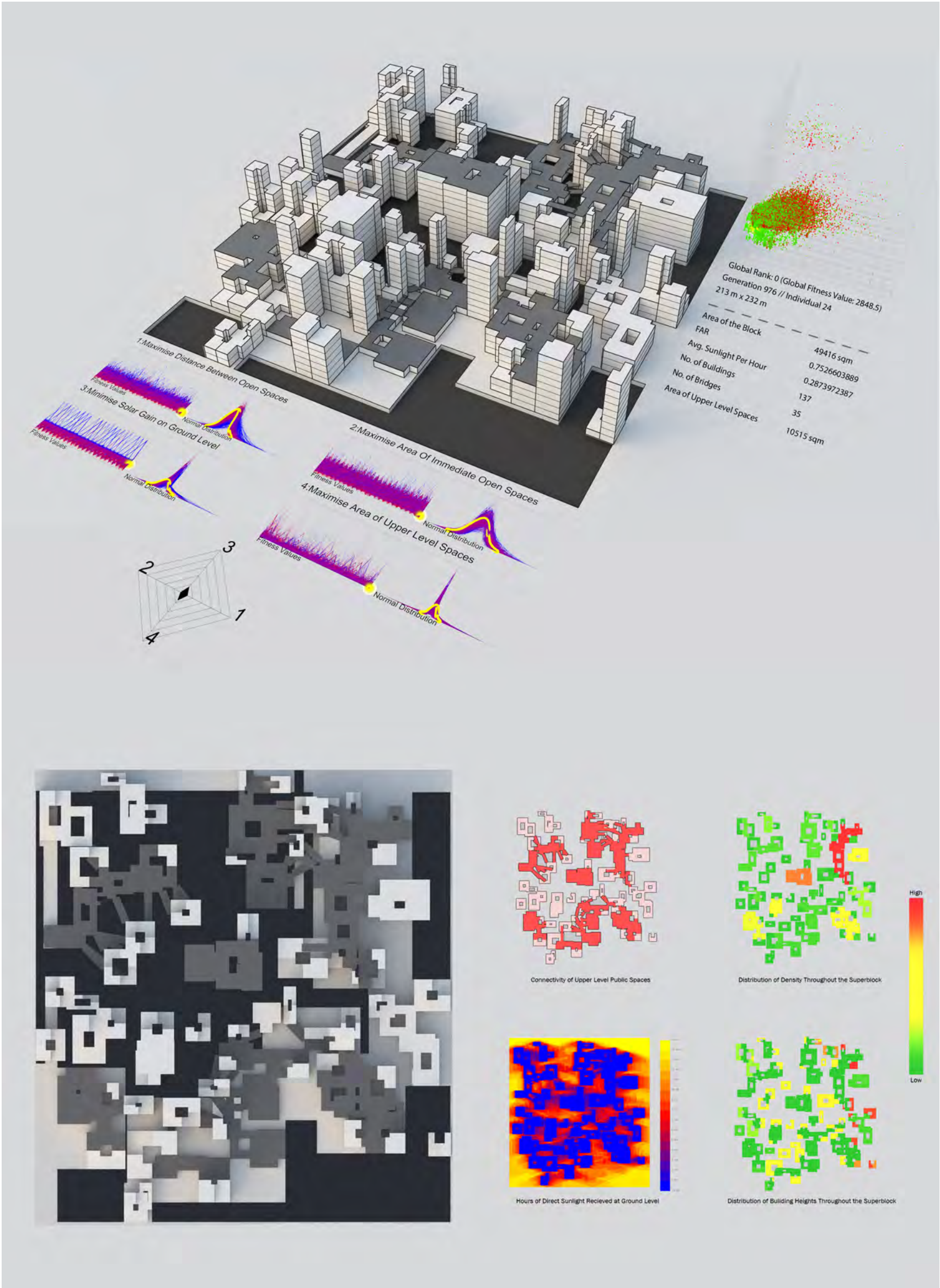
5.32.
Fittest solution for Upper Level
Spaces objective.

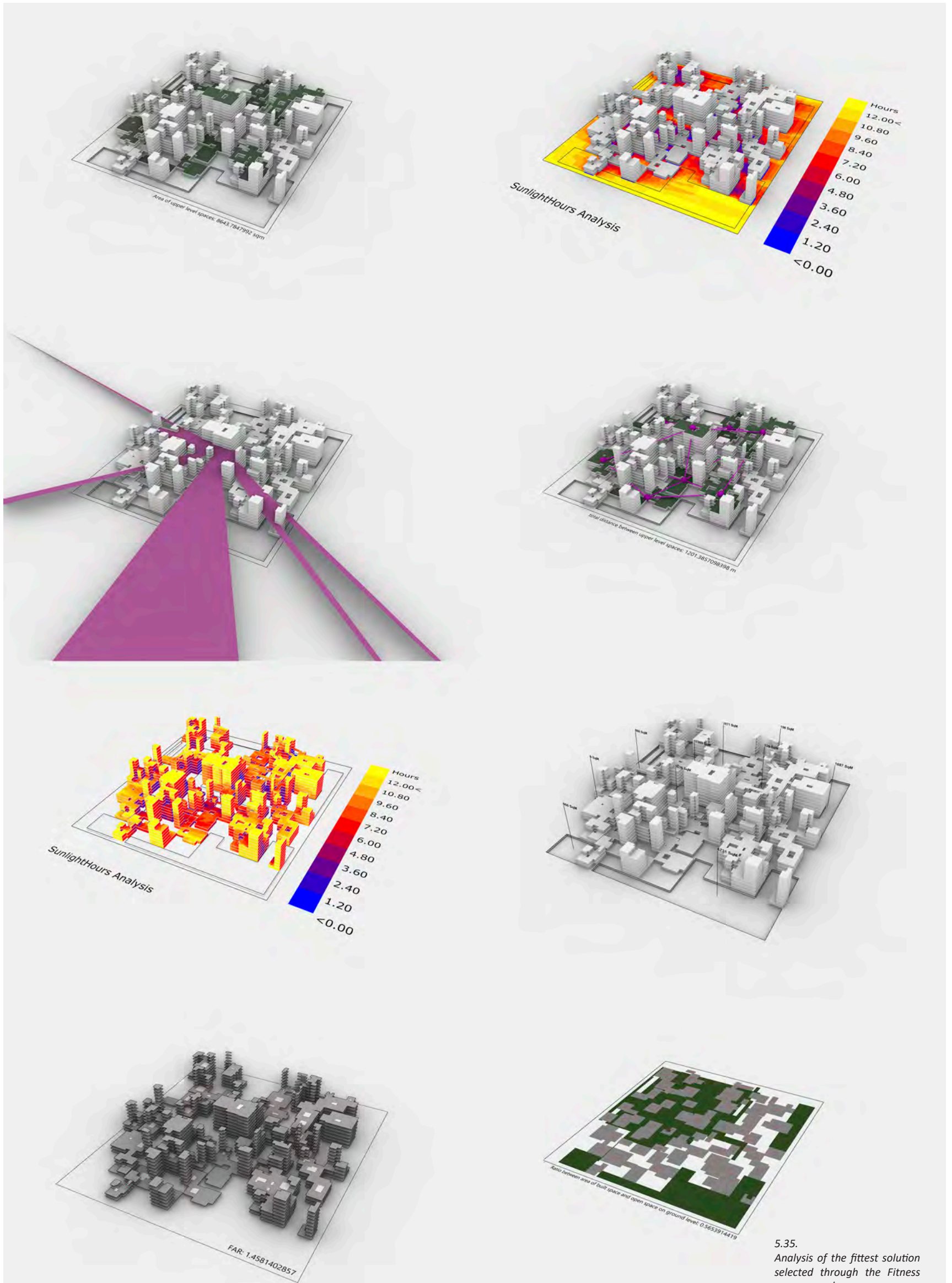


5.33.
Fittest solution for Distance
between all Open Spaces
objective.

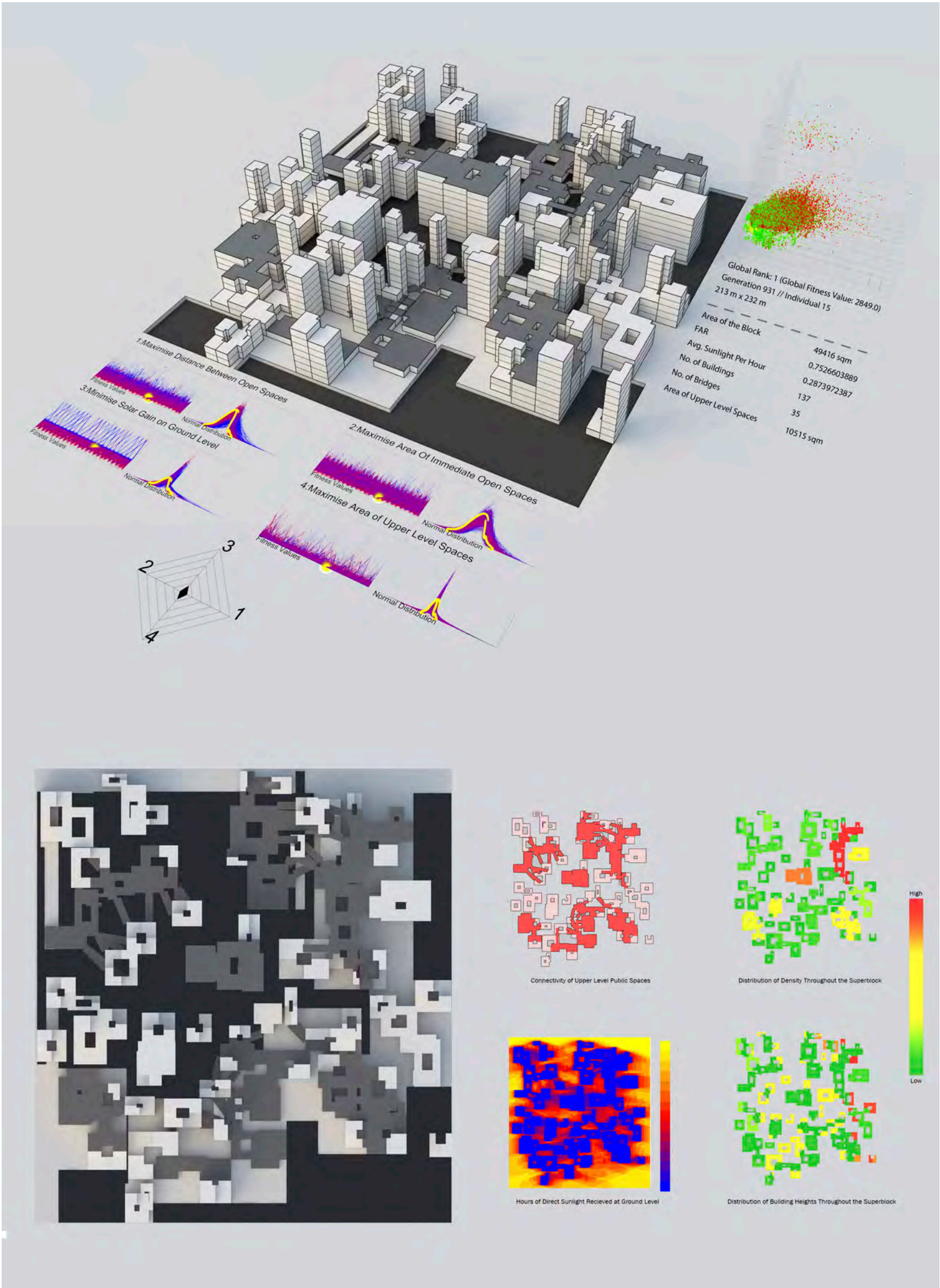


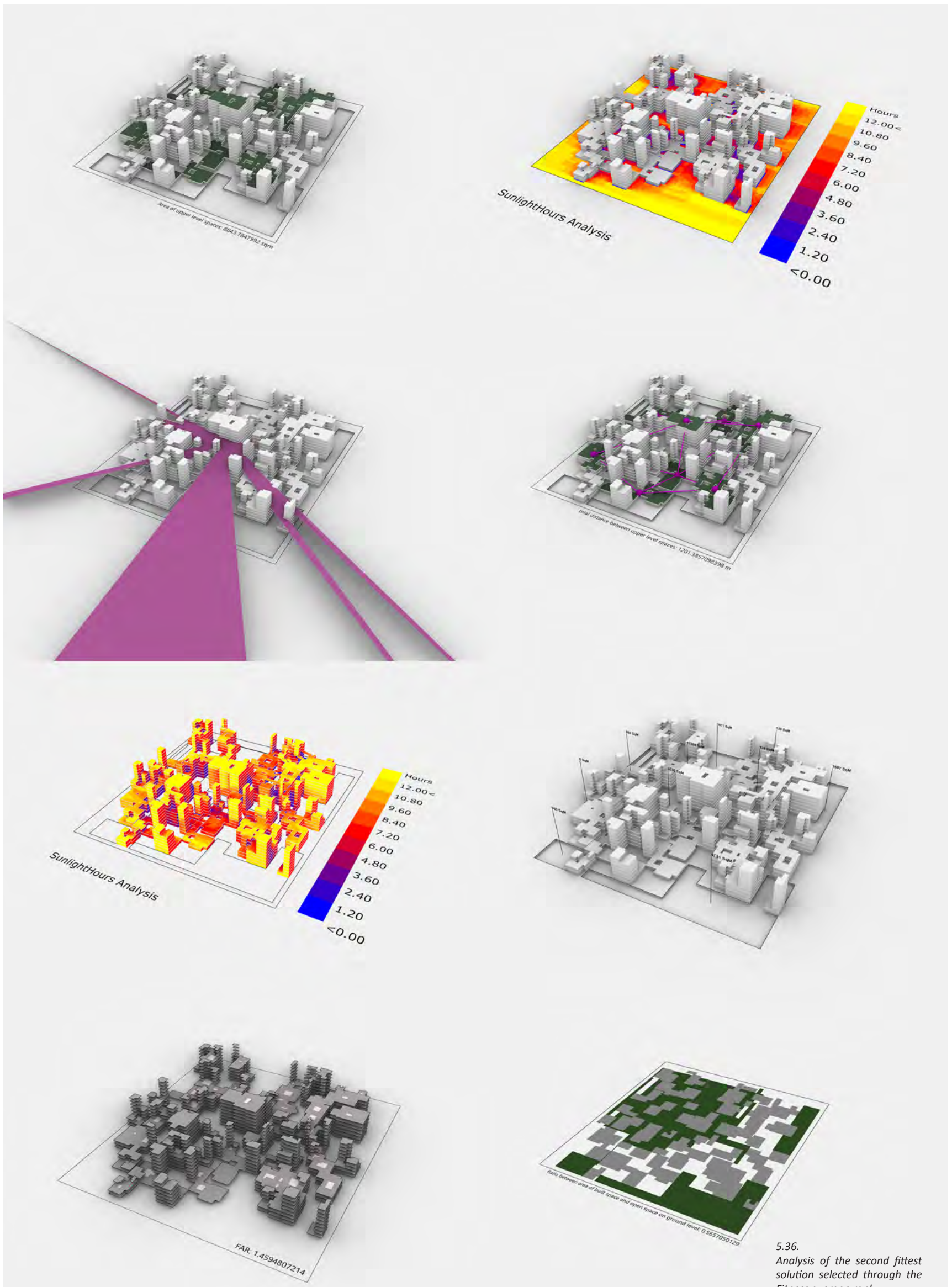
5.34.
Fittest solution for shadow on
ground objective.



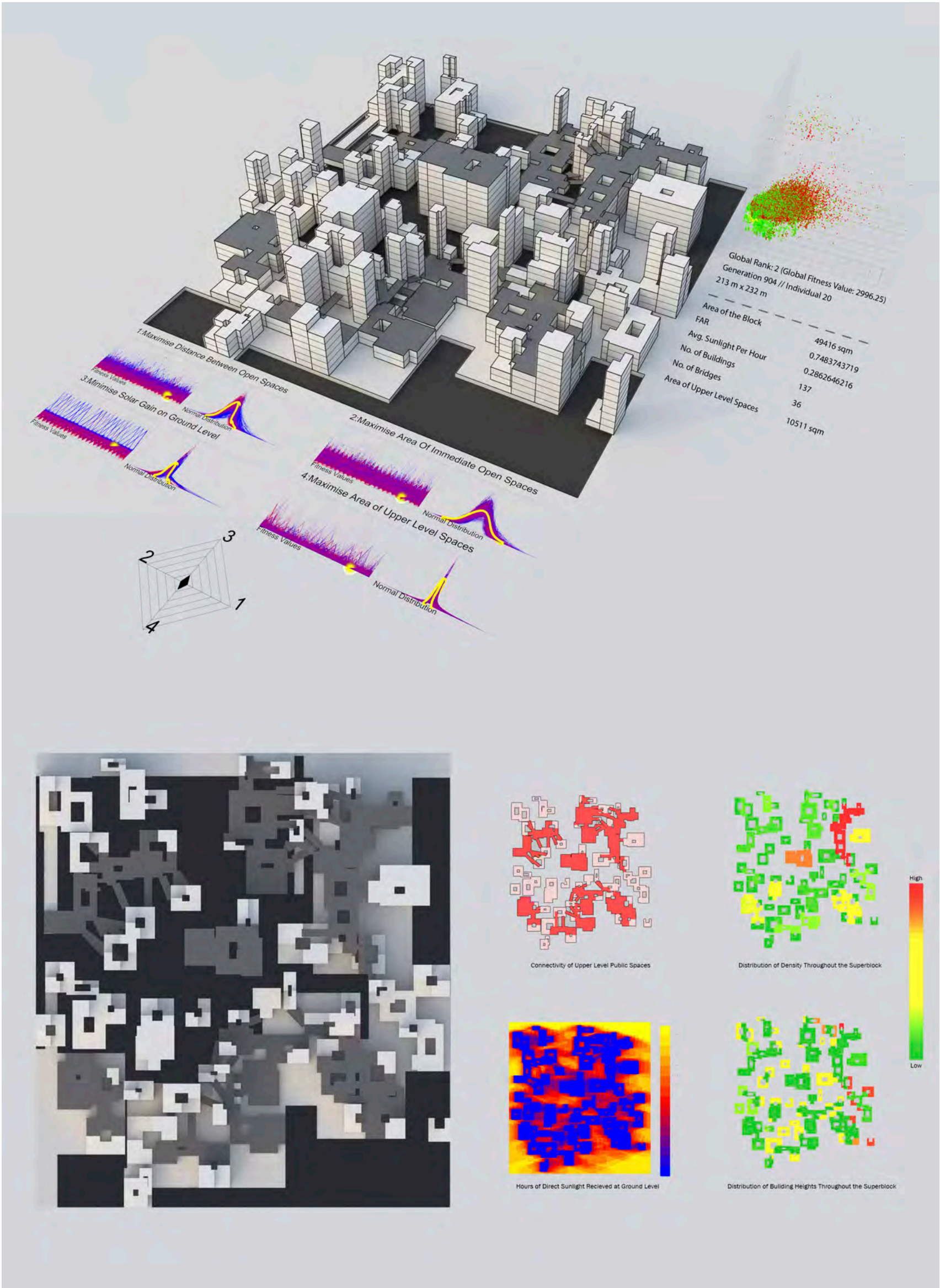


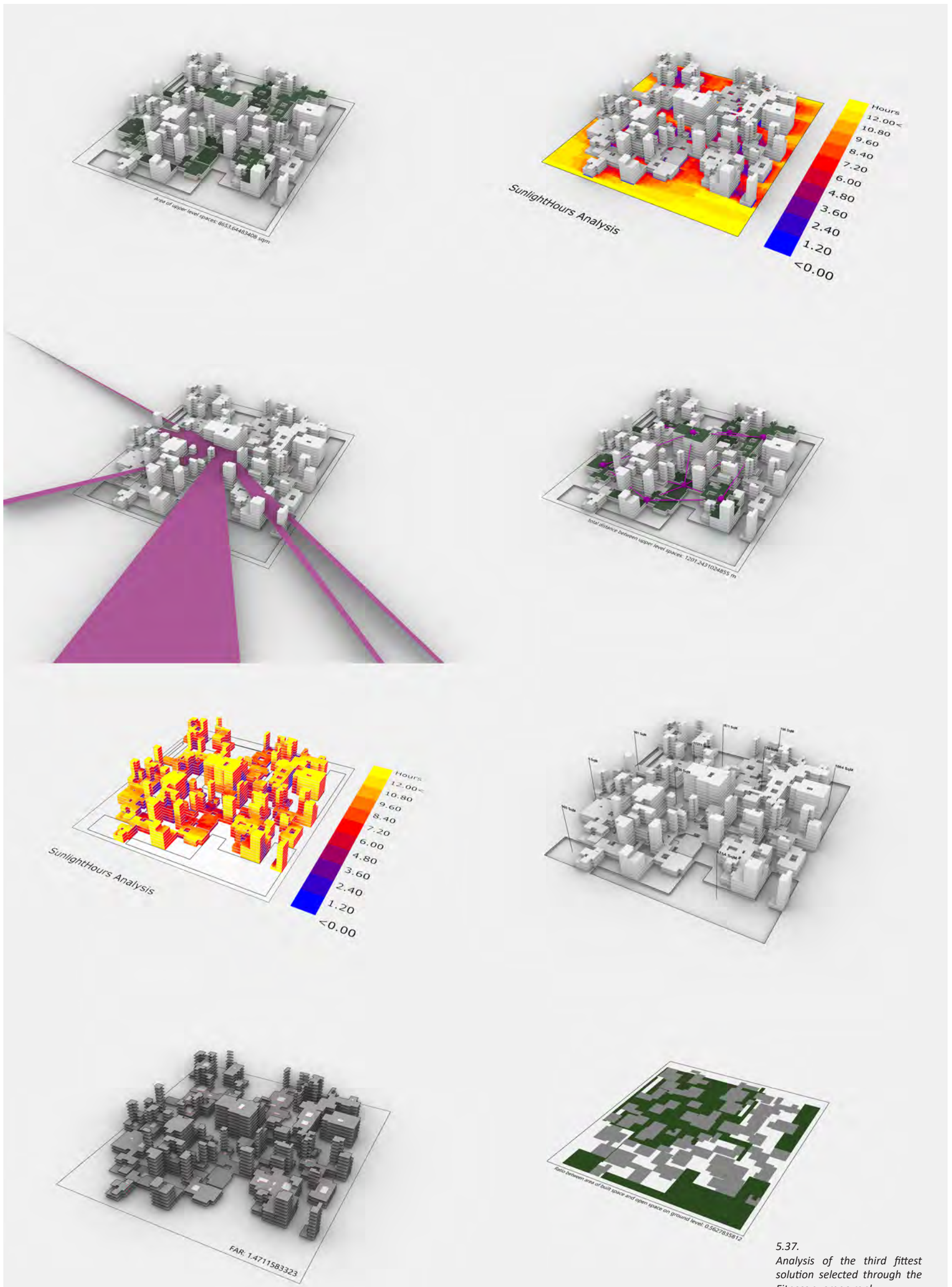
5.35.
Analysis of the fittest solution
selected through the Fitness
average rank.



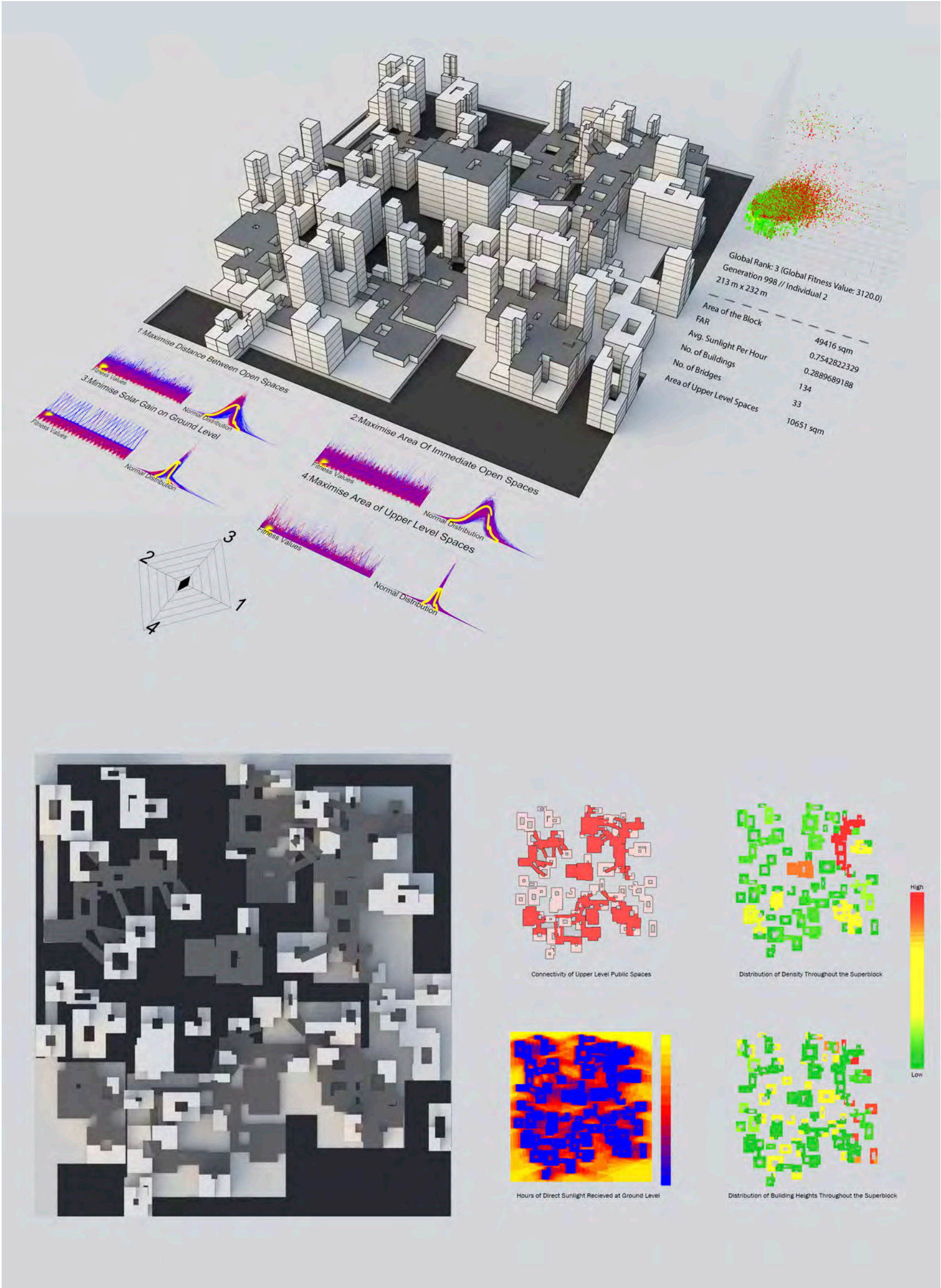


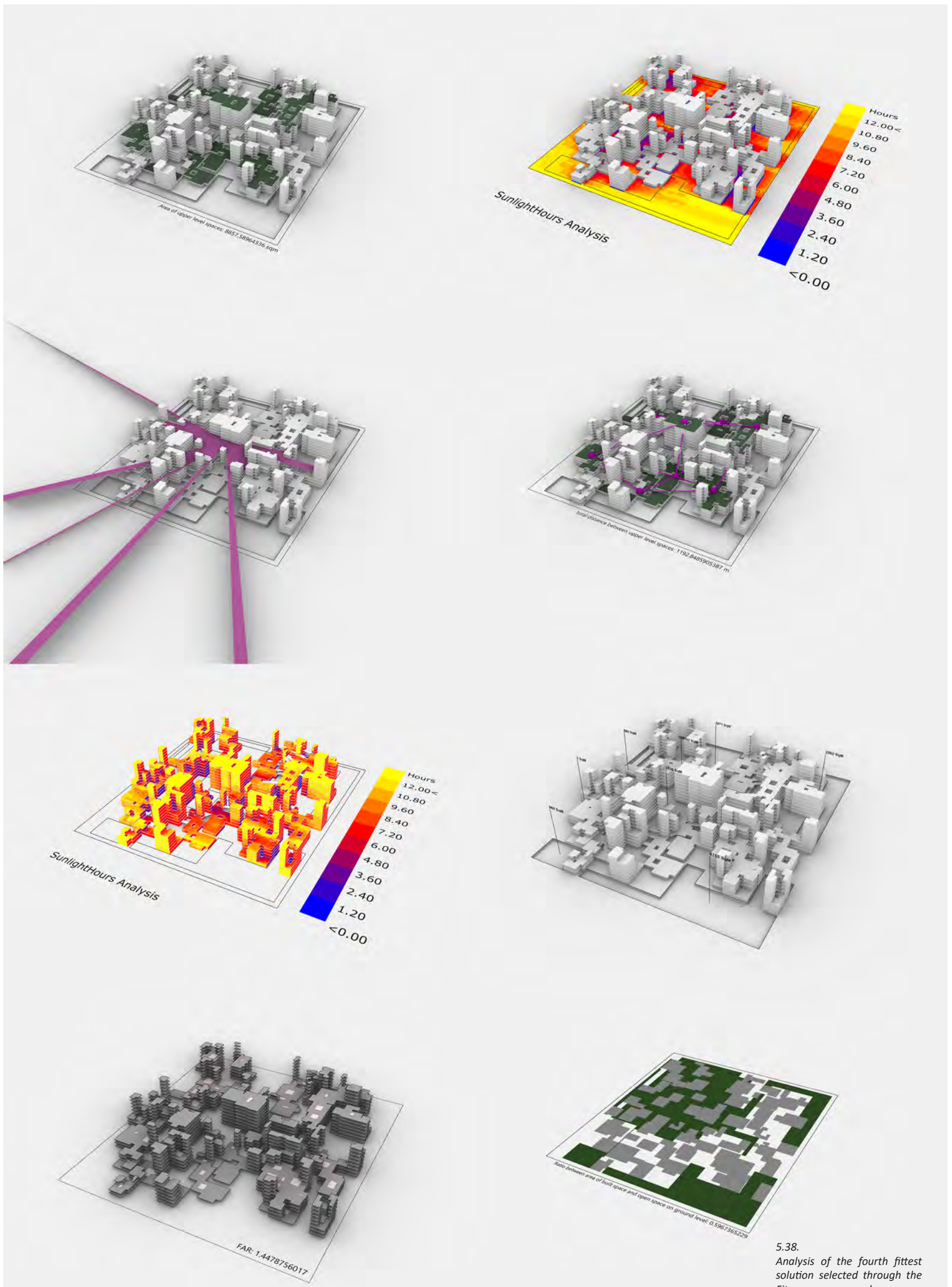
5.36.
Analysis of the second fittest
solution selected through the
Fitness average rank.

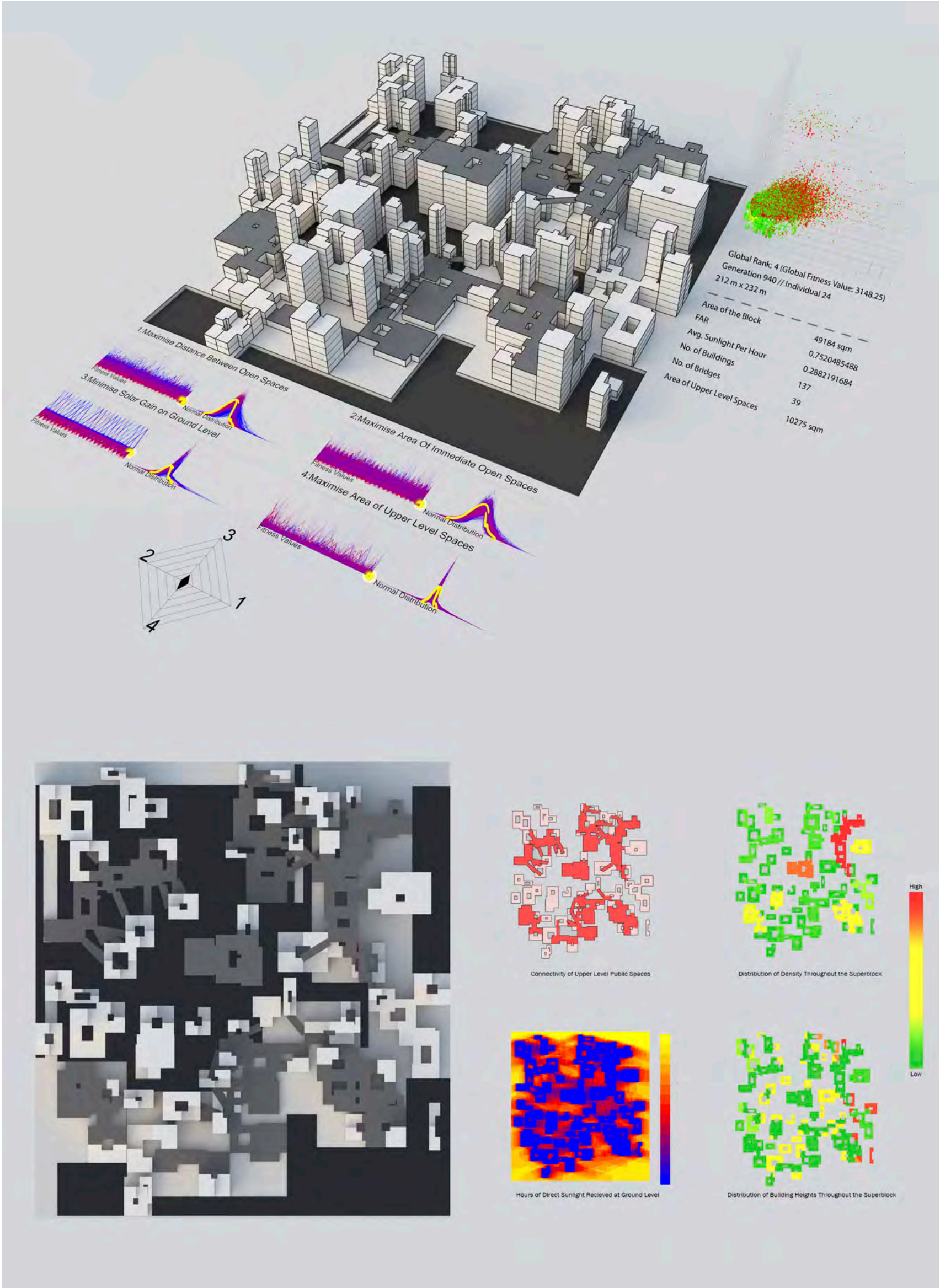


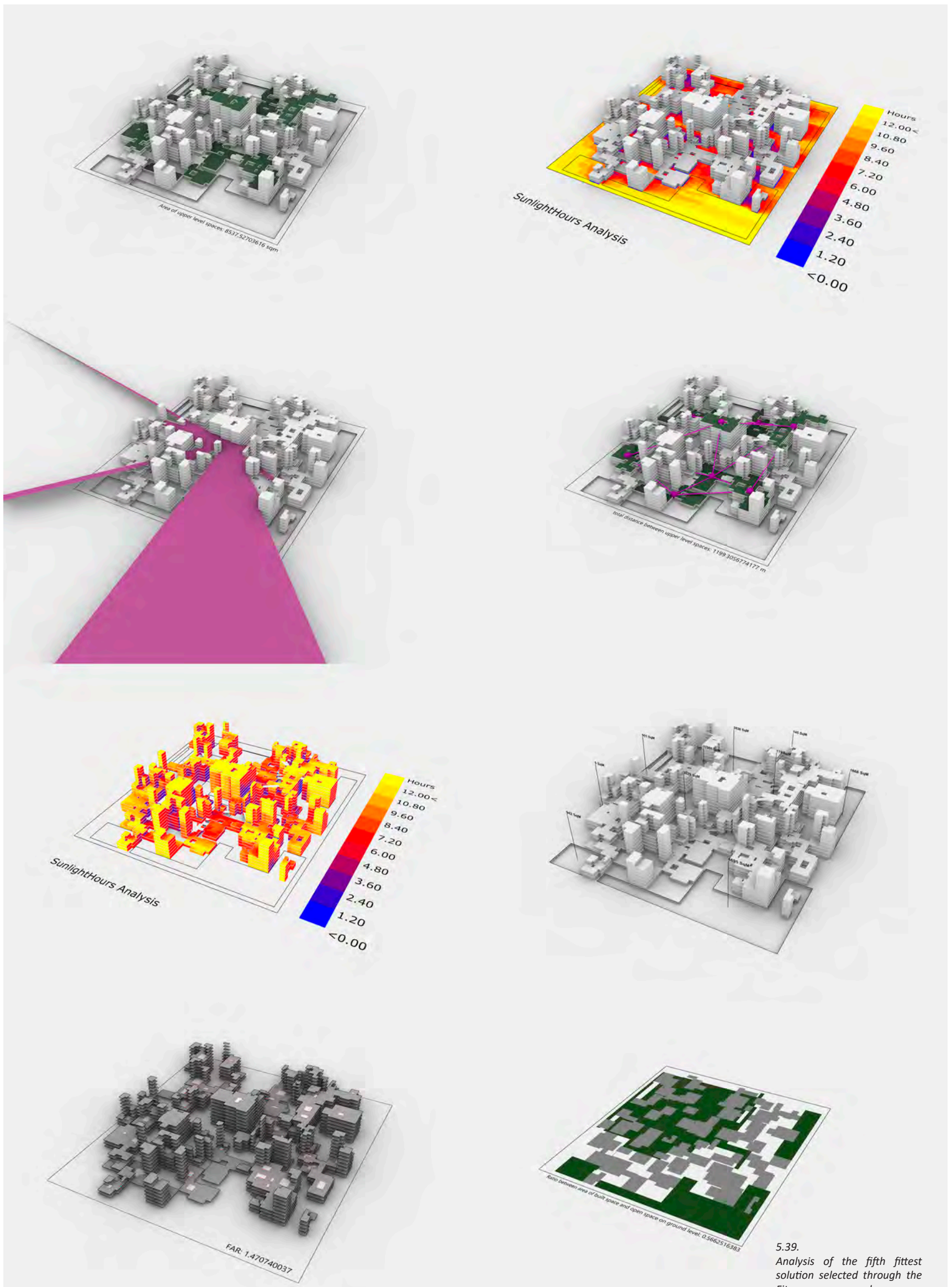


5.37.
Analysis of the third fittest
solution selected through the
Fitness average rank.

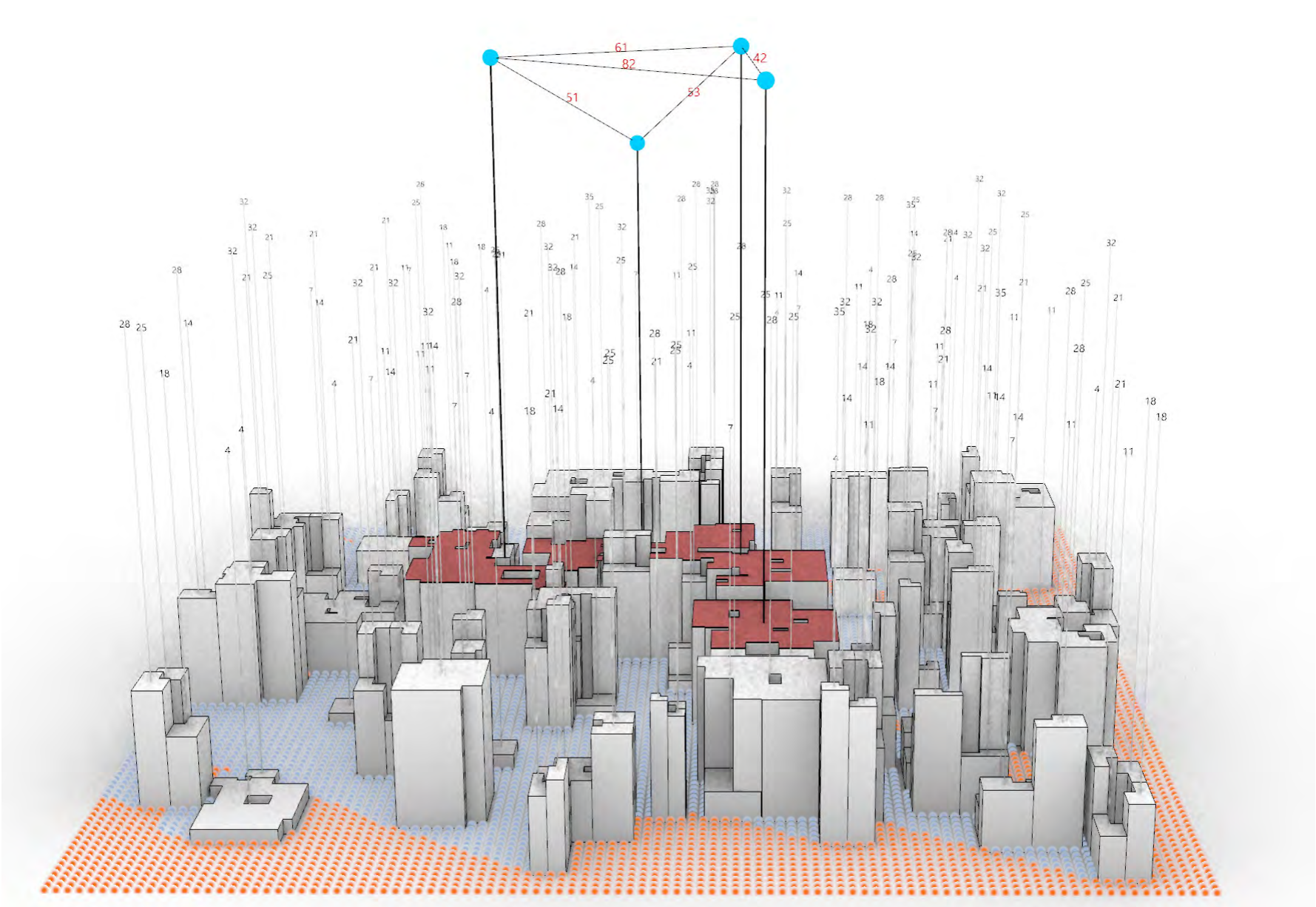




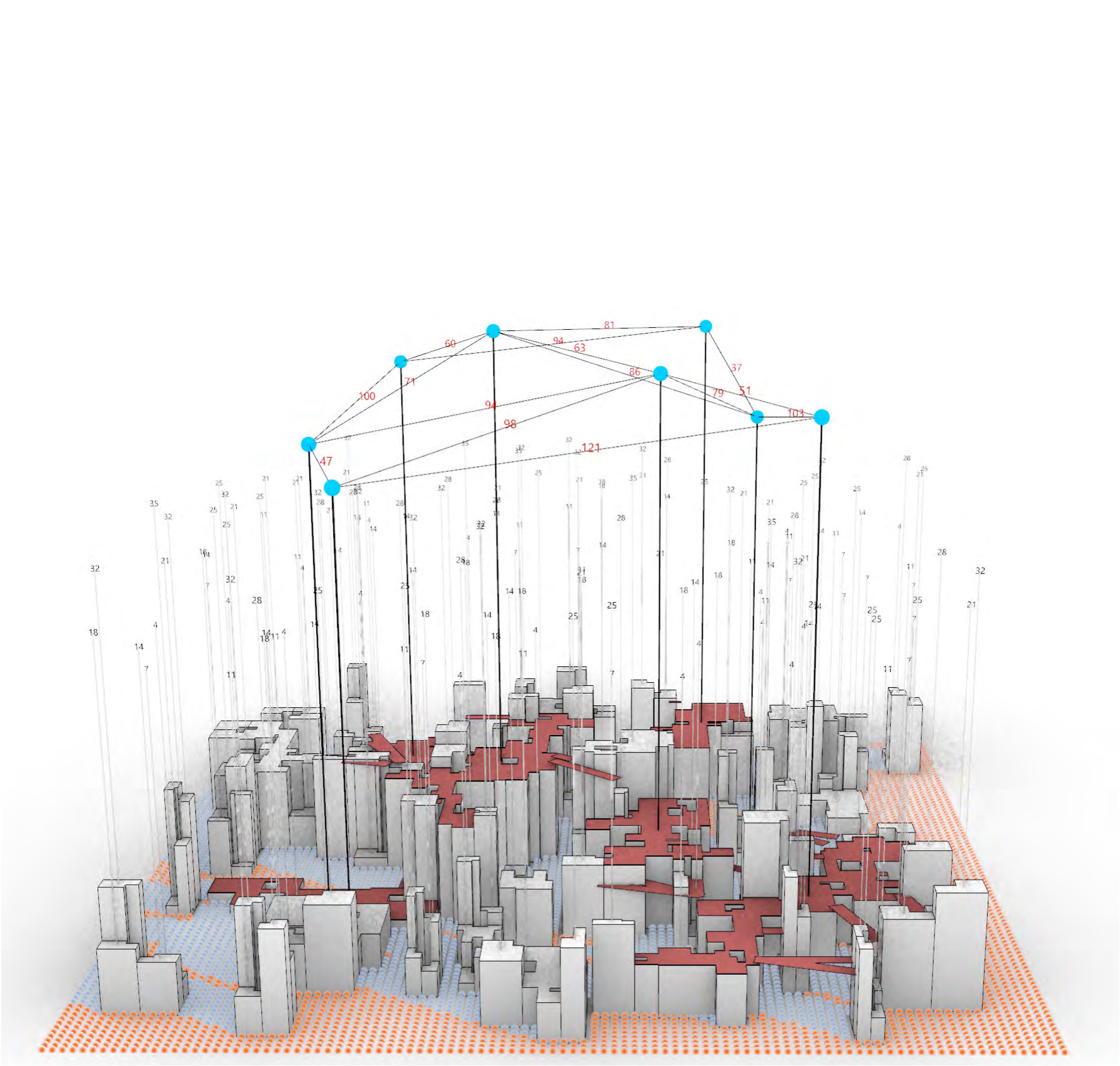


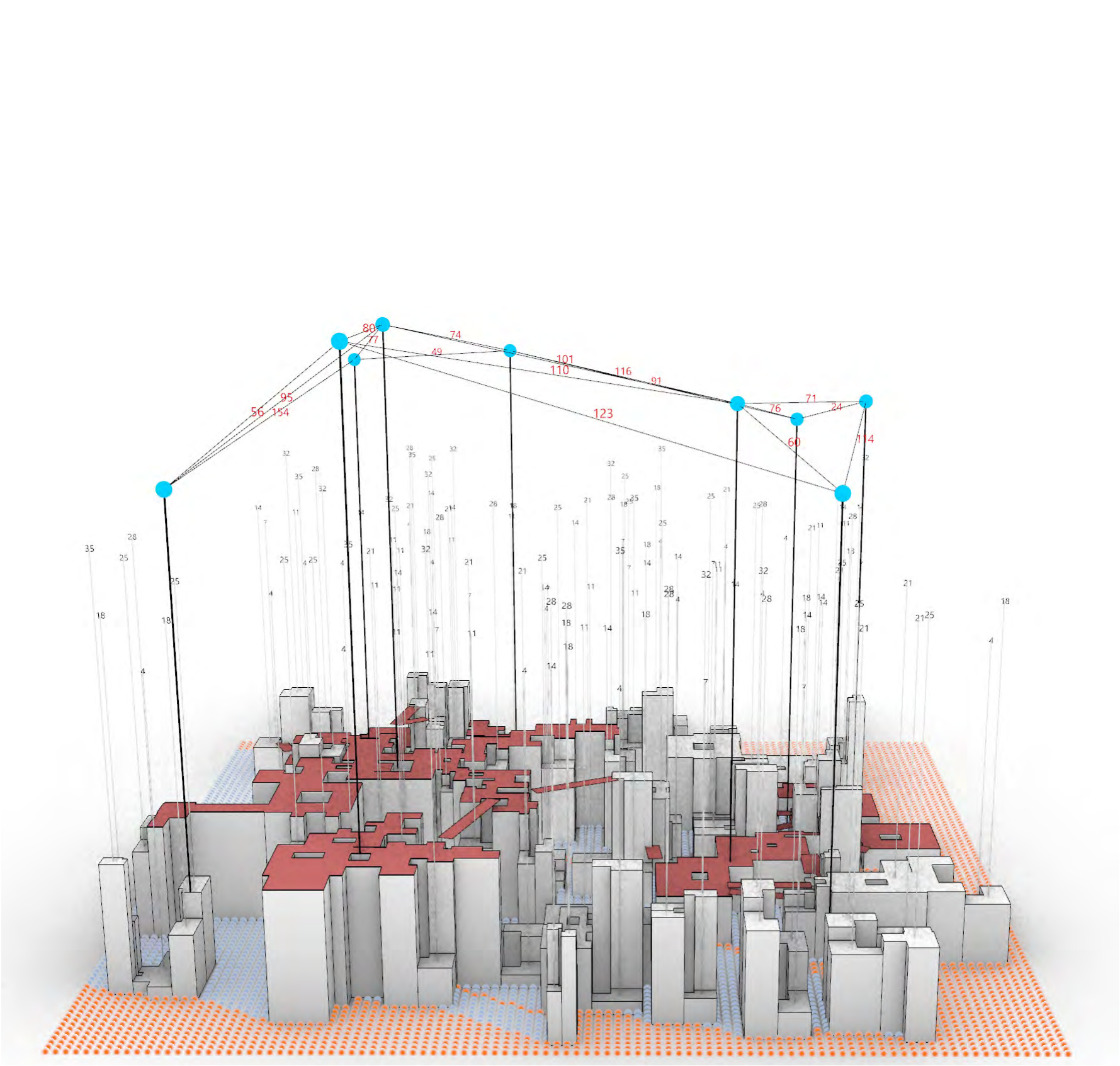


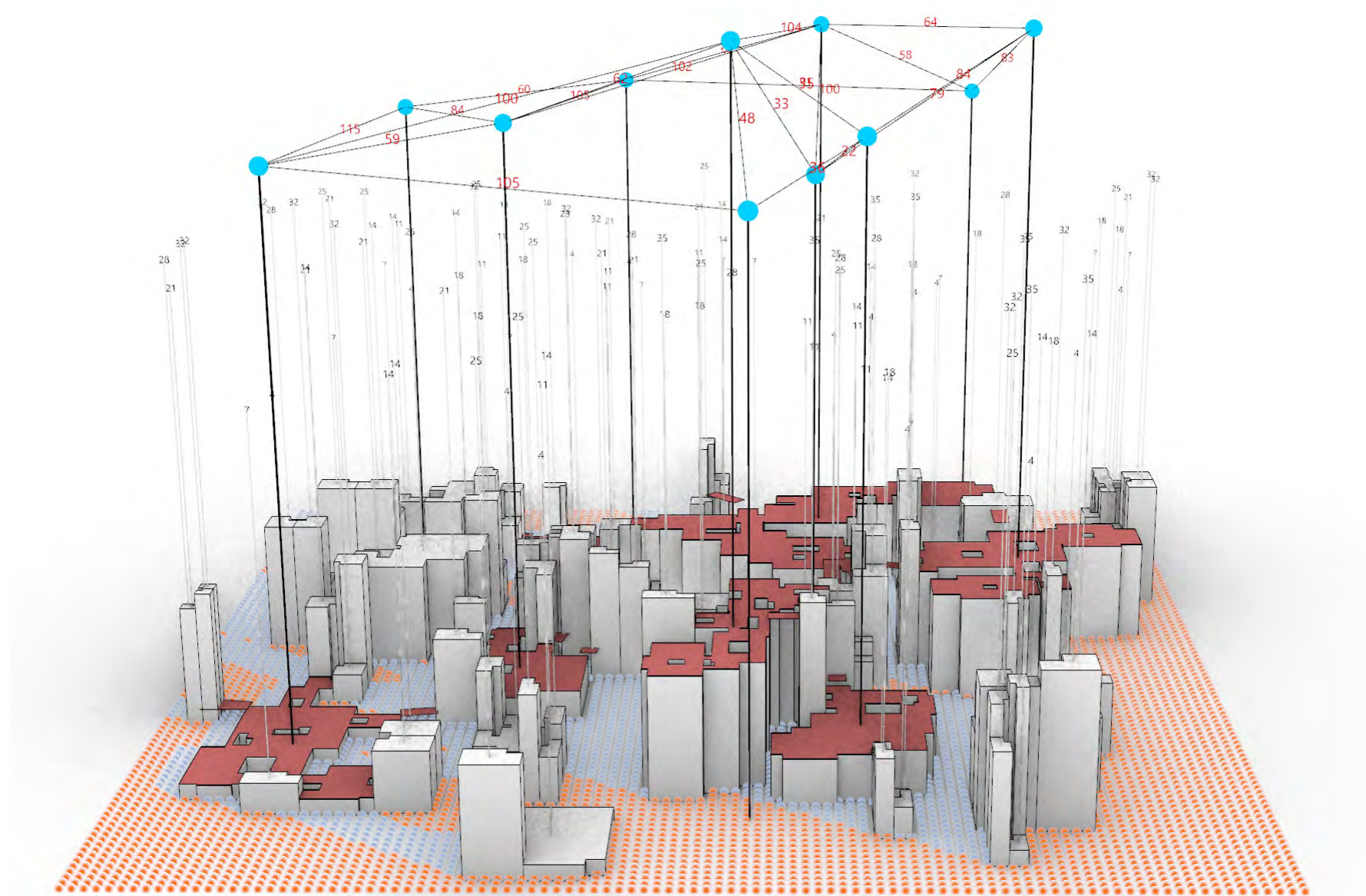
5.39.
Analysis of the fifth fittest
solution selected through the
Fitness average rank.

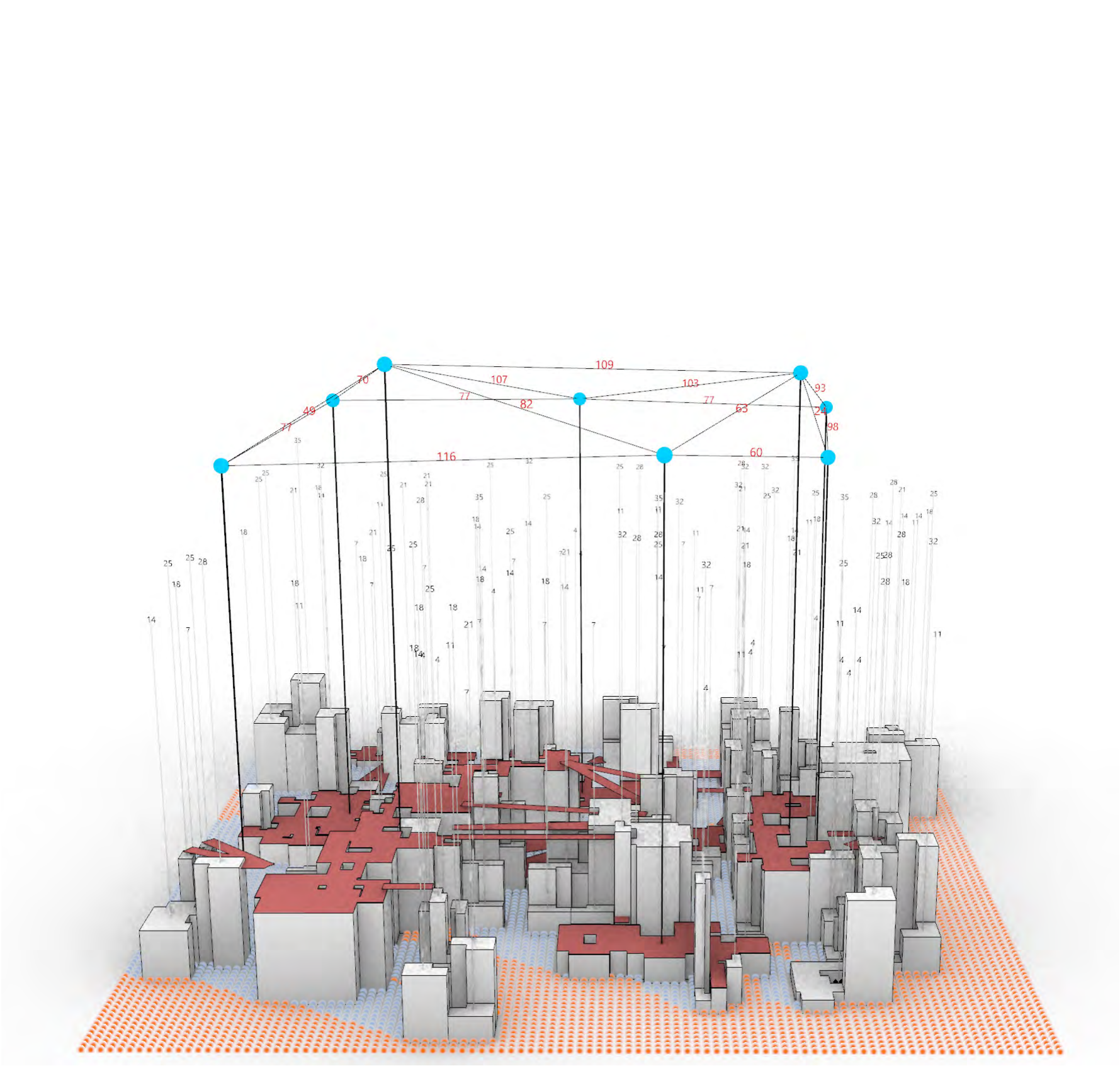


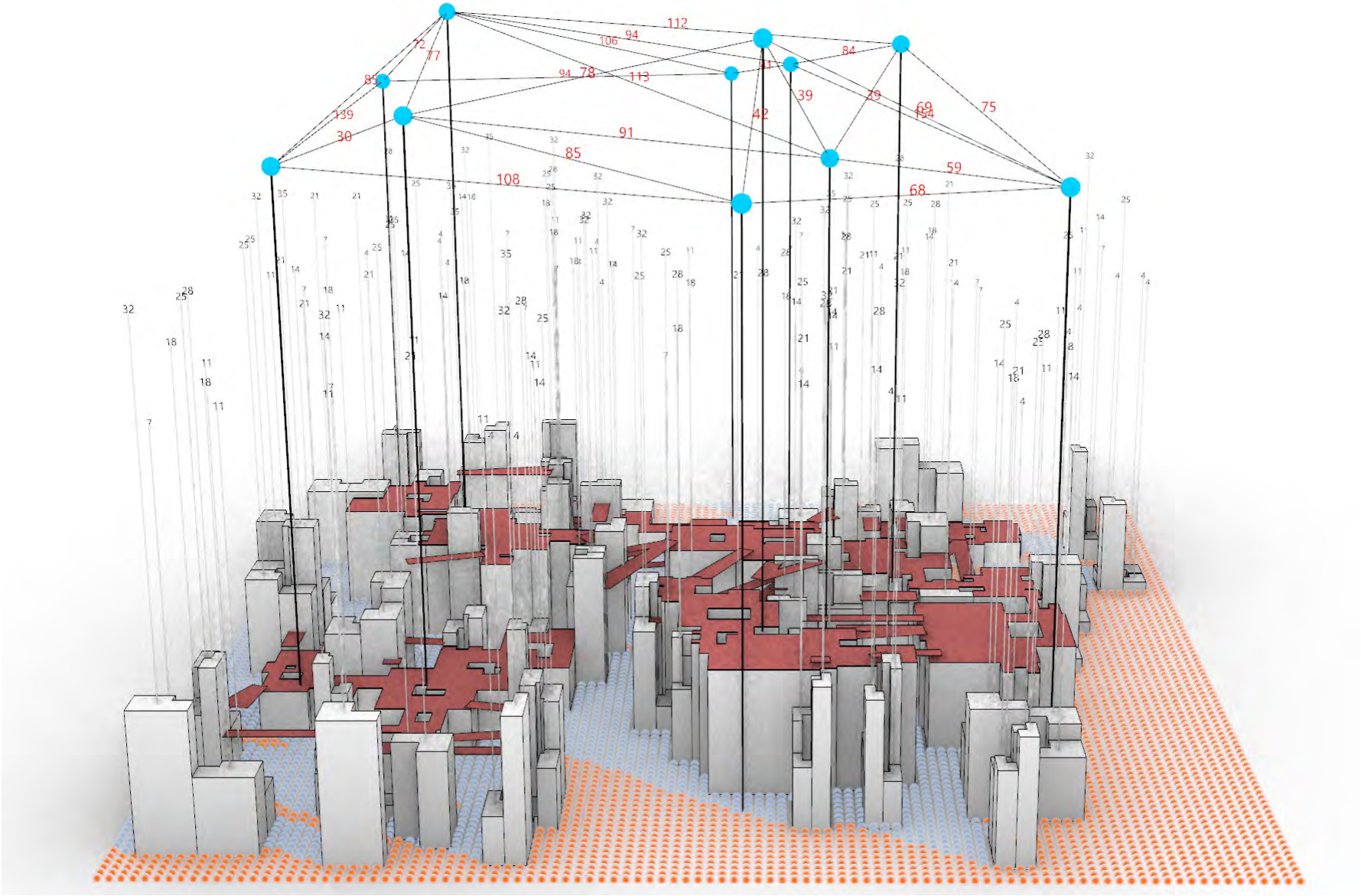
5.40 - A to J.
Analysis of the Ground Solar Gain, Upper level Walkways, Building Heights (representing density) and Distance and Distribution between lower level and upper level open spaces through a selection of supeblocks evolved by the simulation.

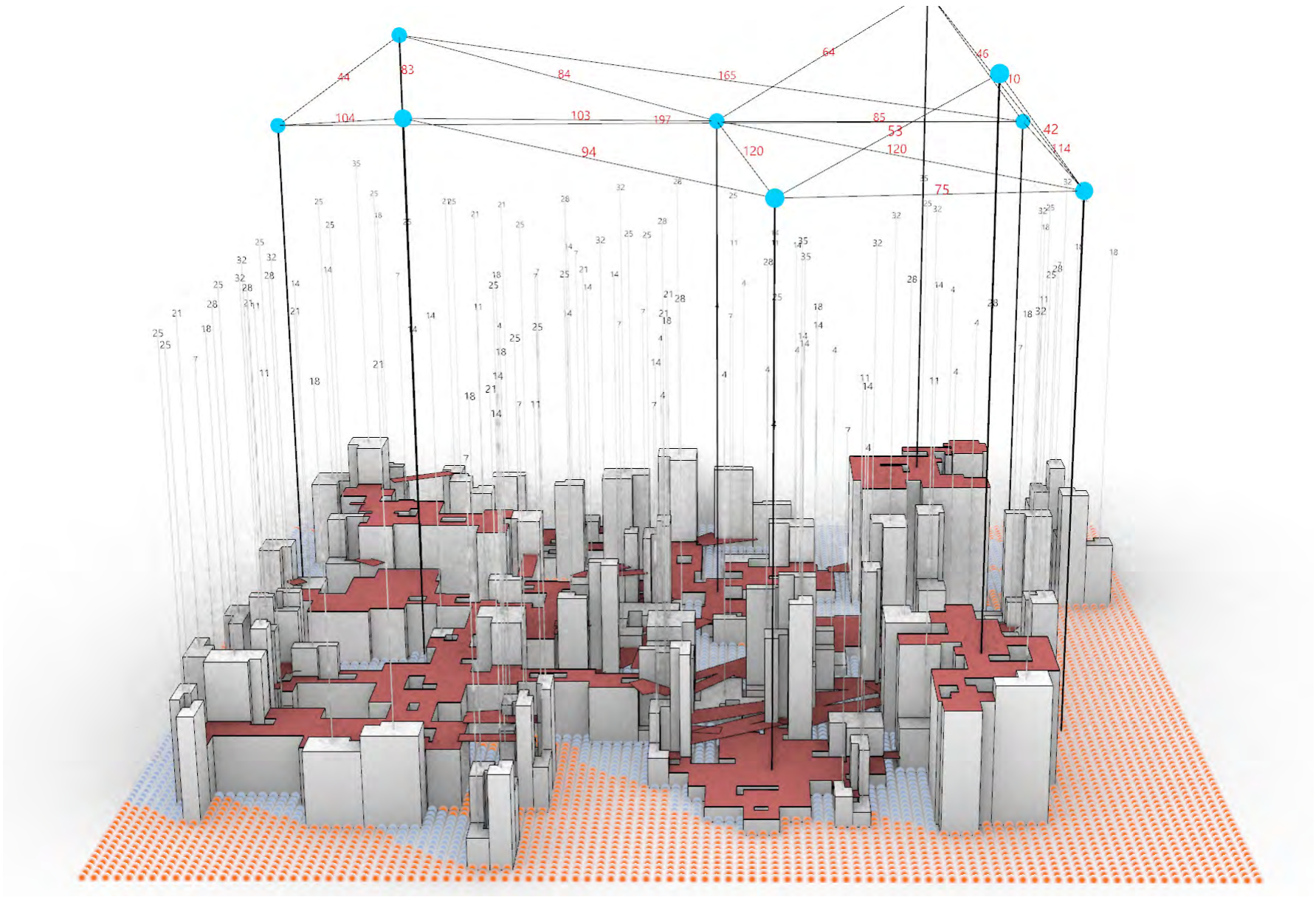


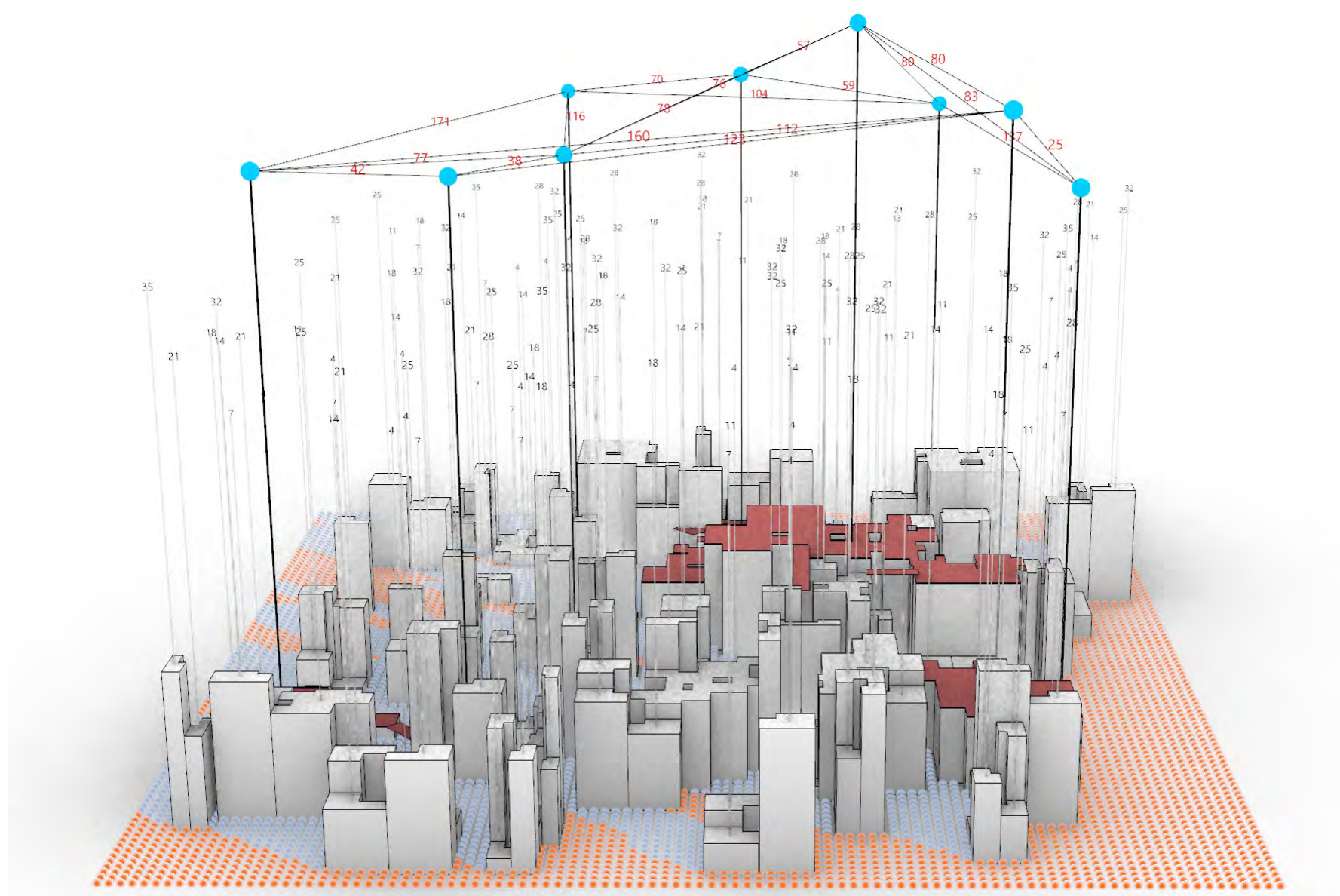


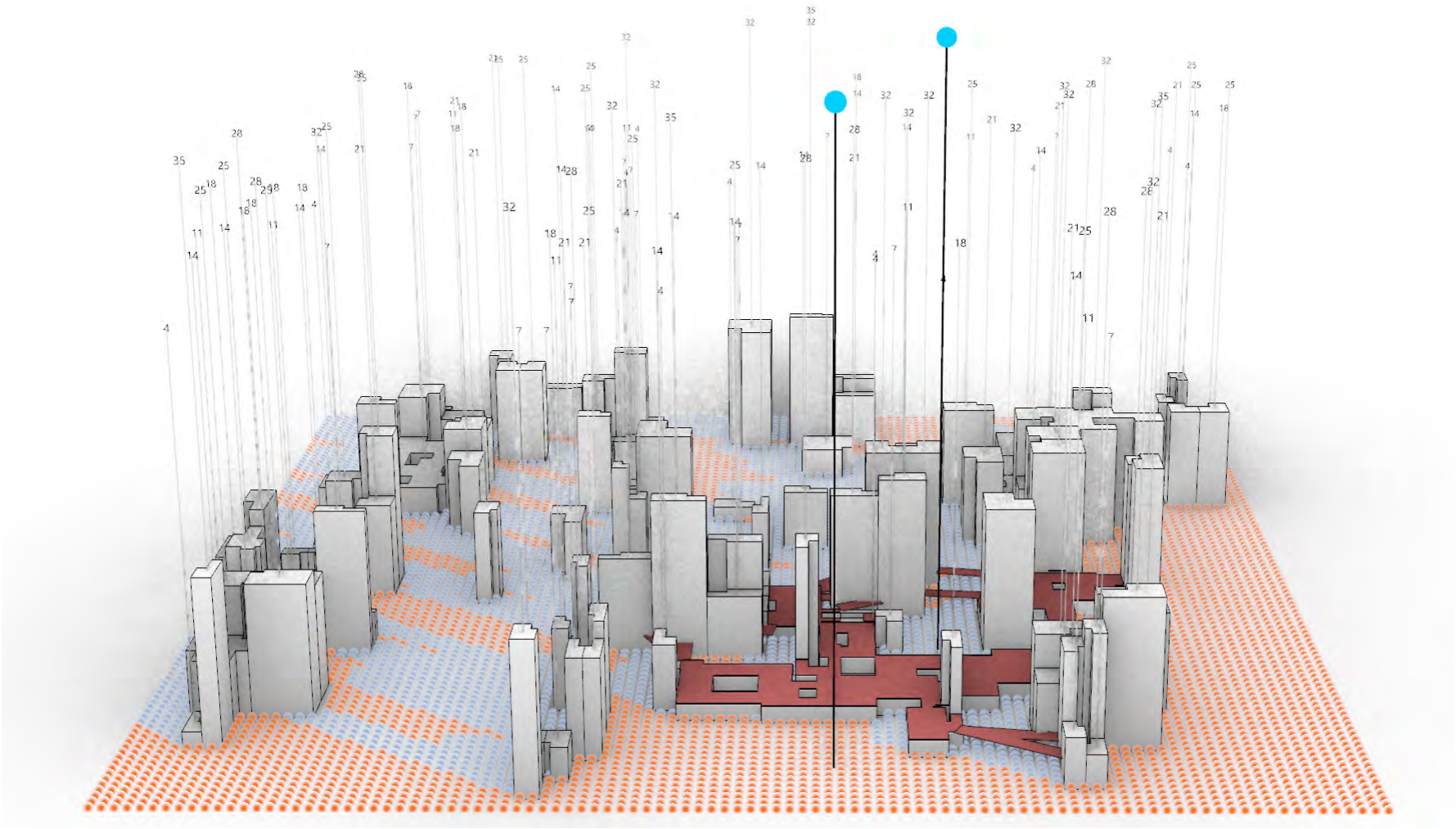


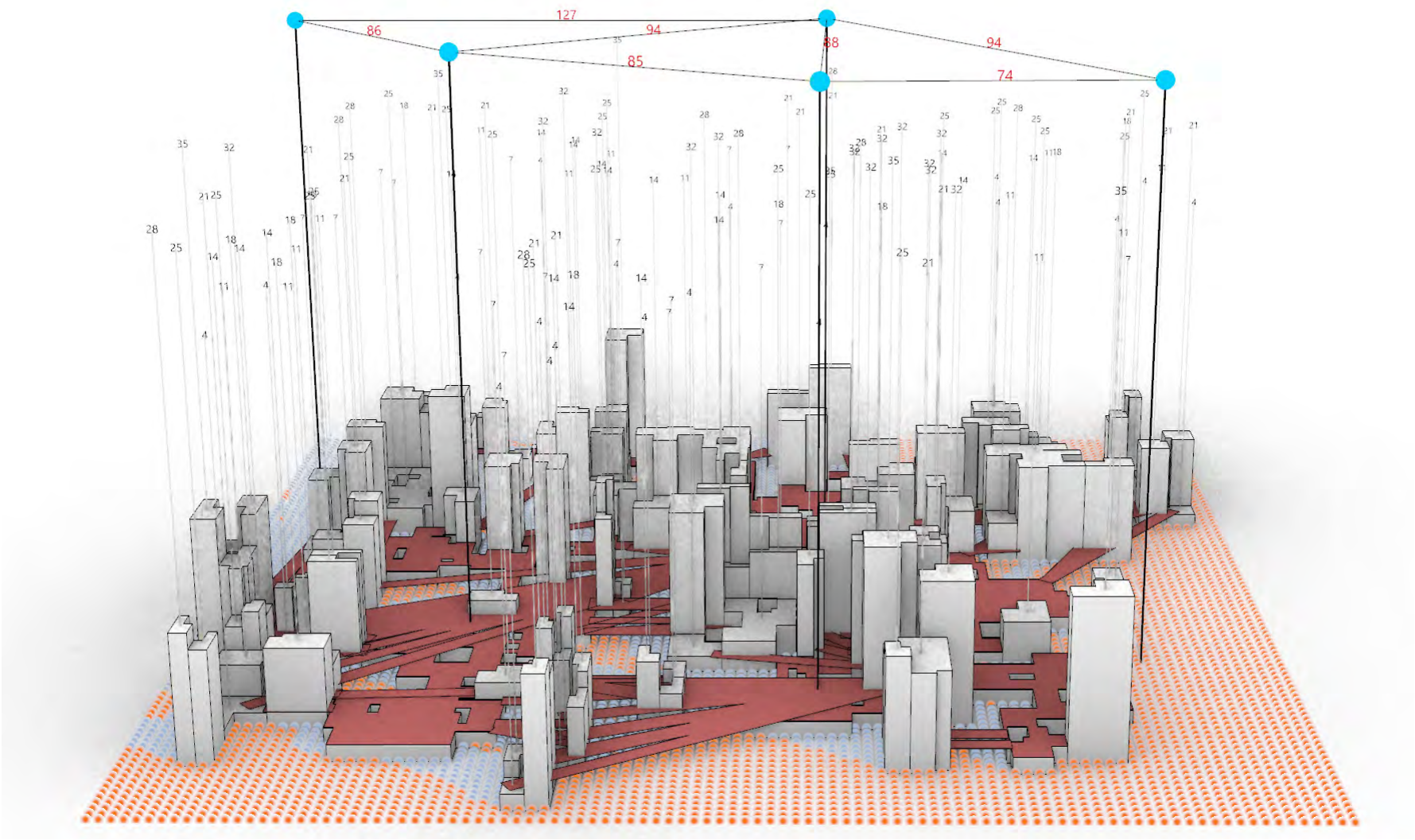


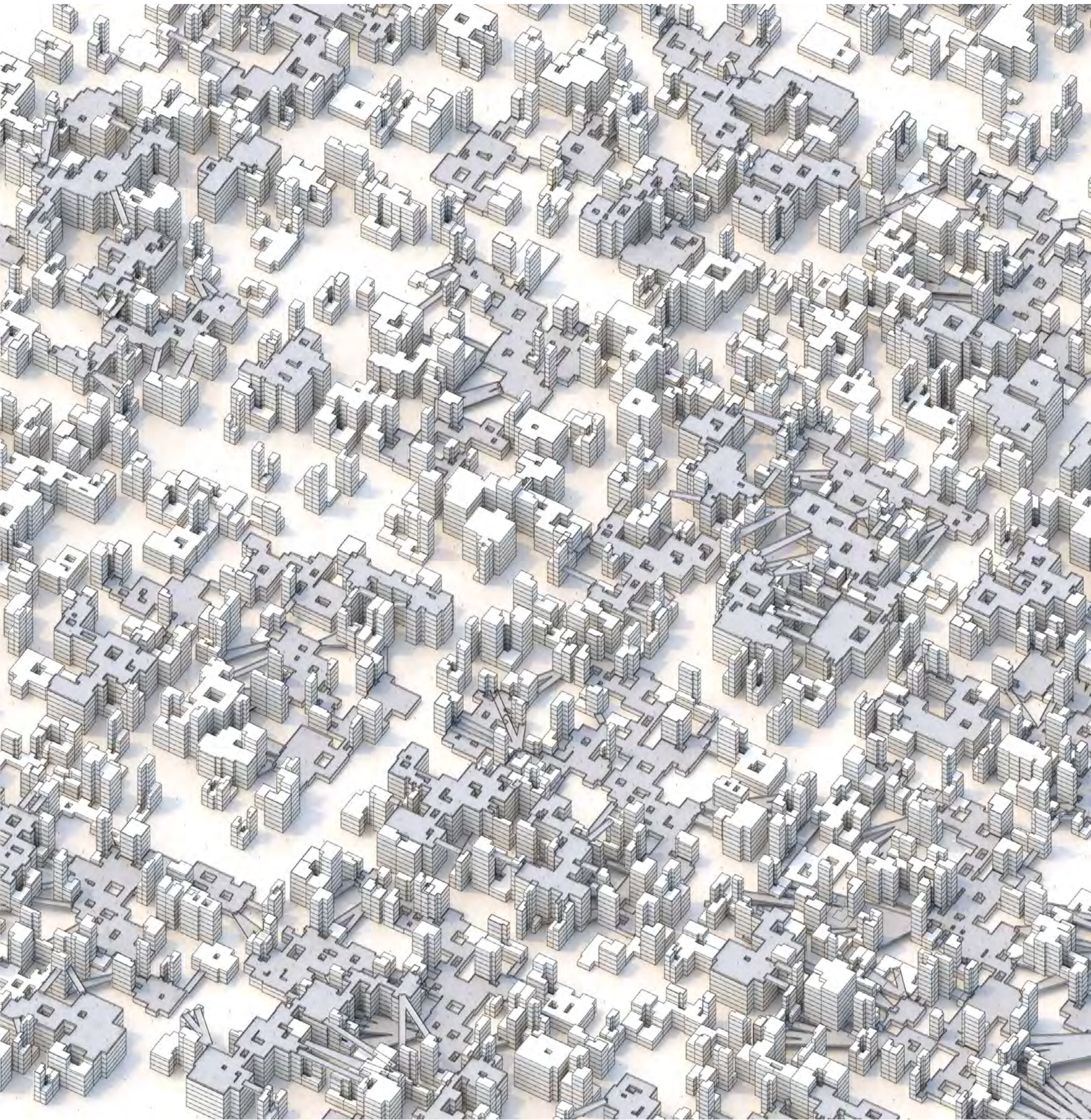




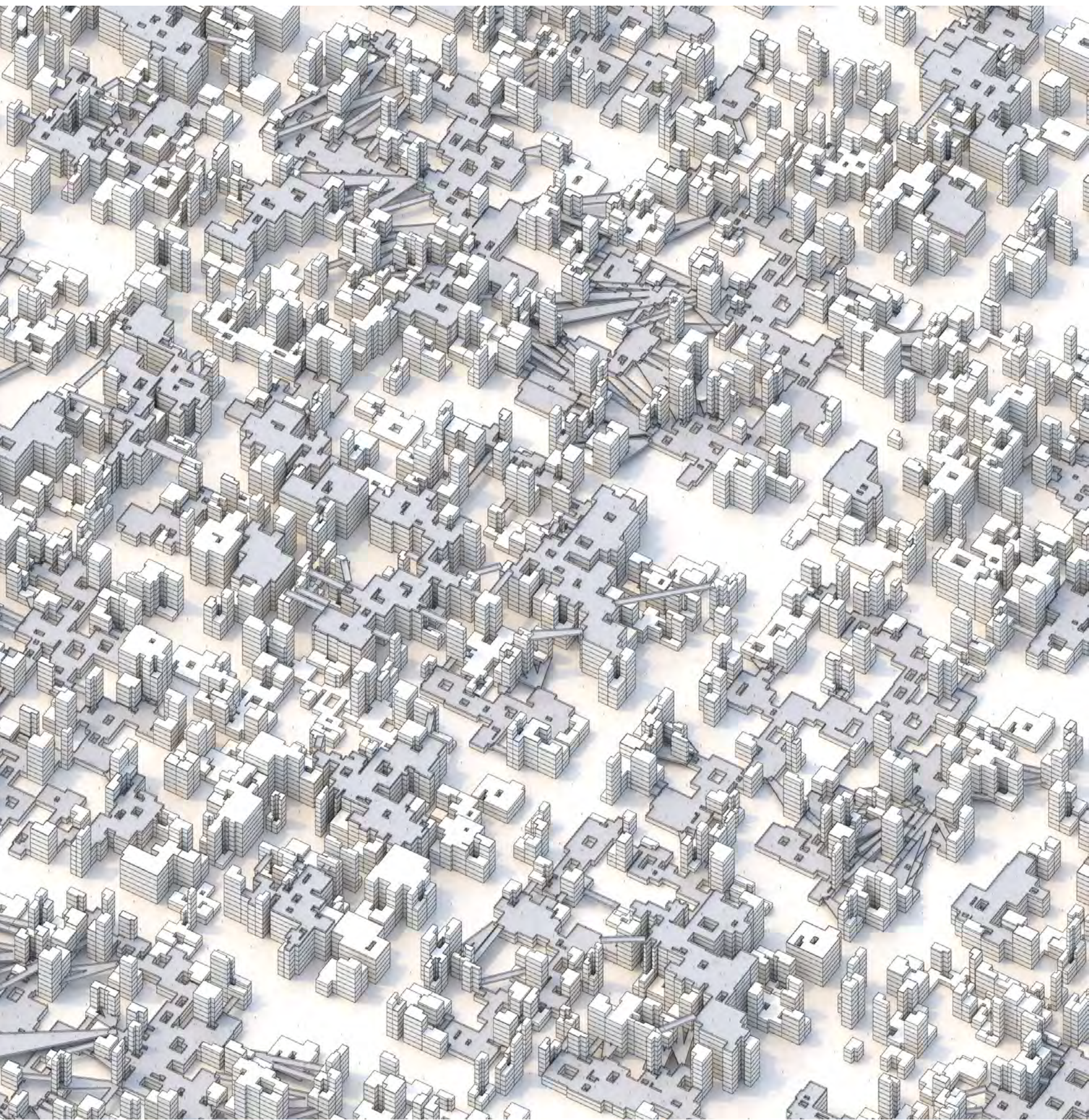


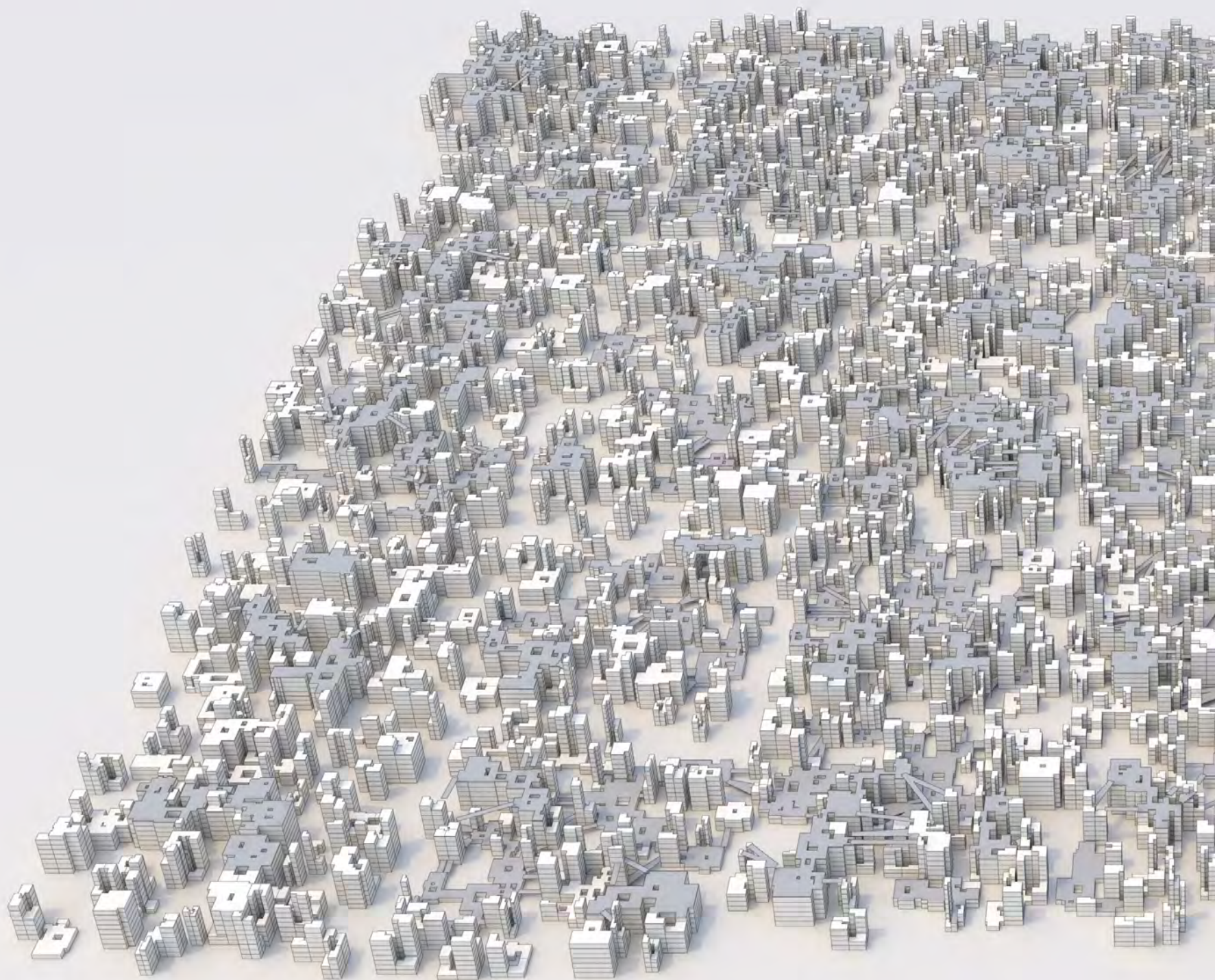


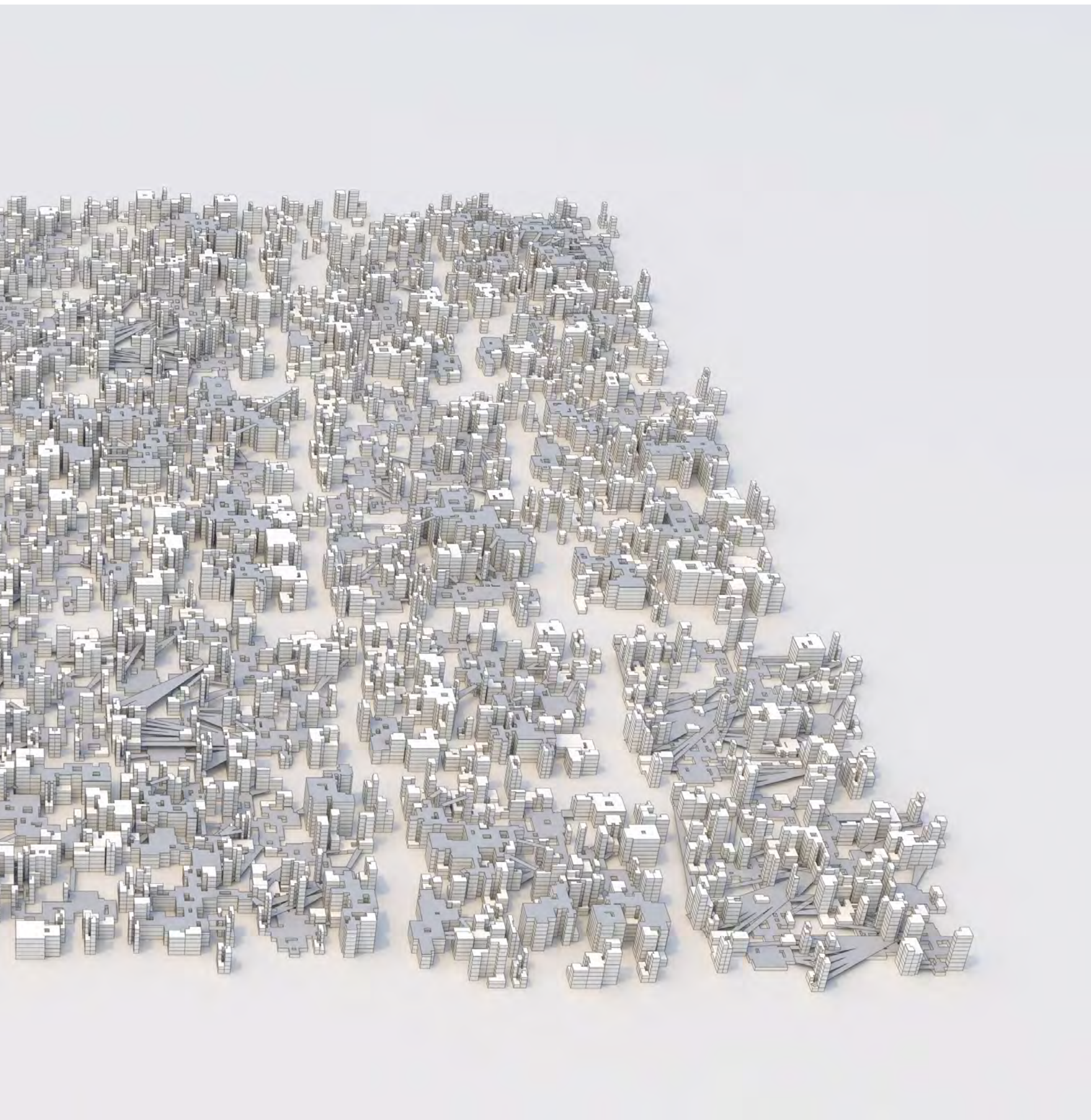


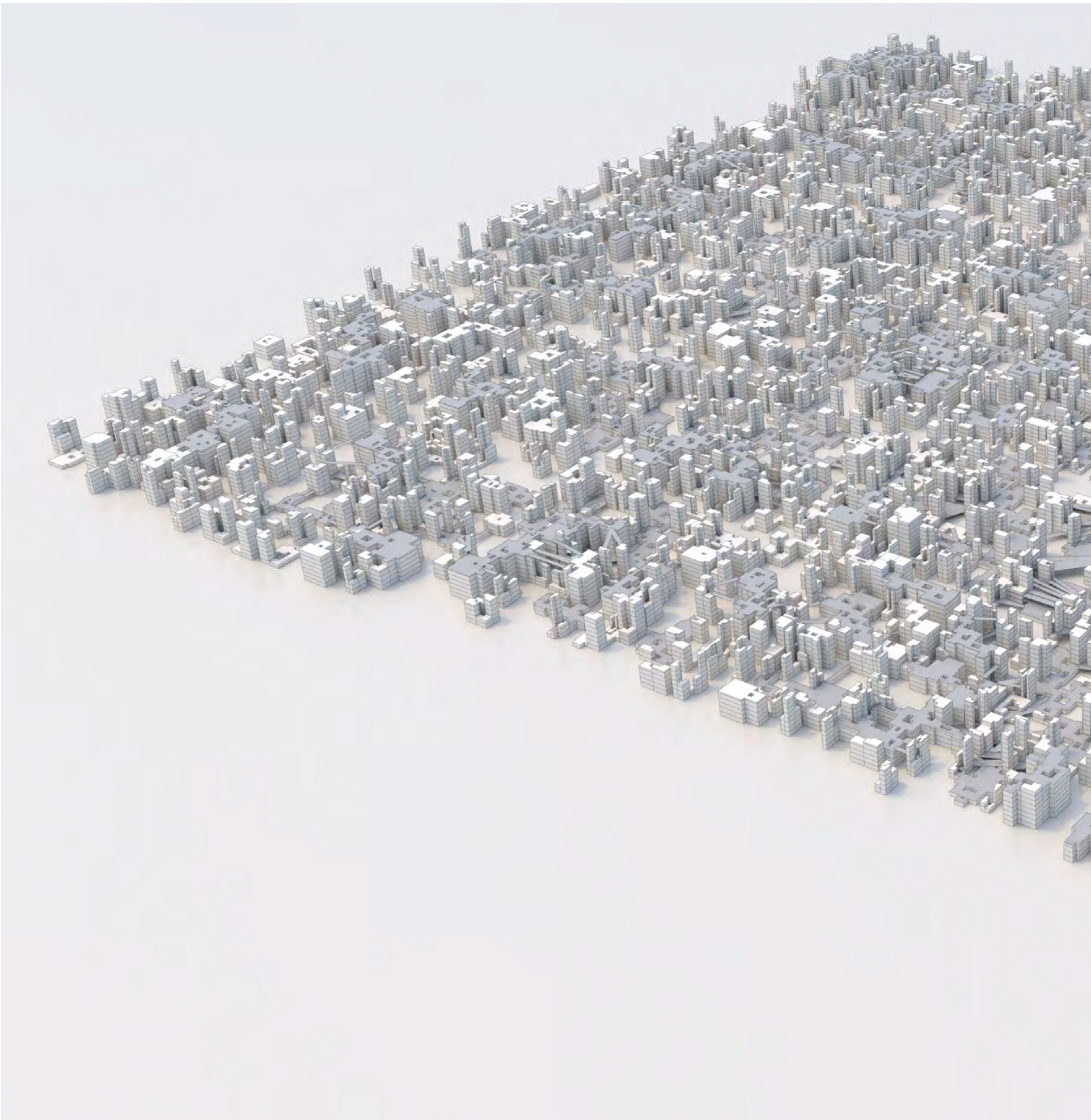


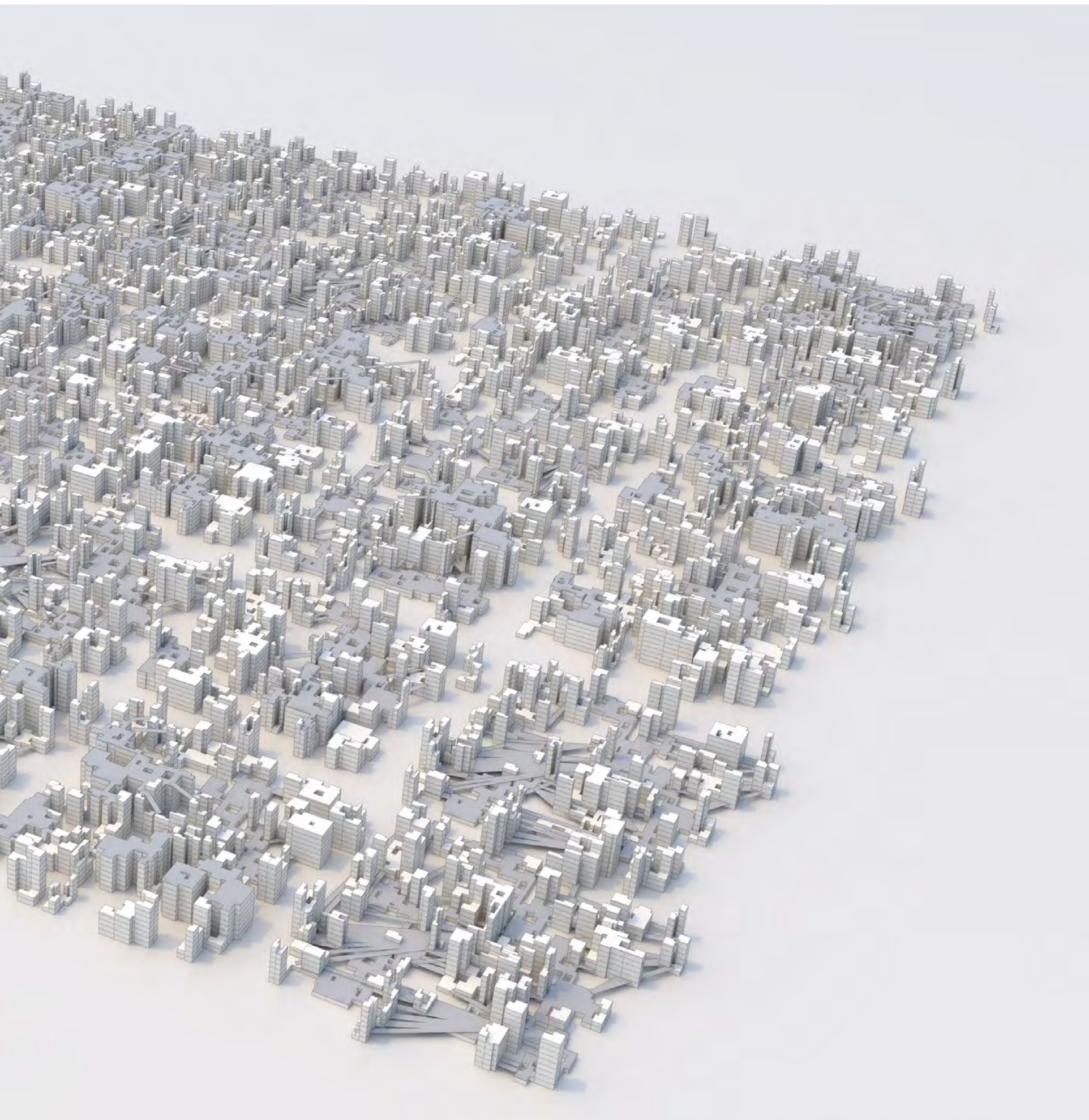
5.41. - A to D
*Distribution of evolved
superblocks within an urban
tissue presenting the levels of
variation found throughout
and between the generated
solutions.*





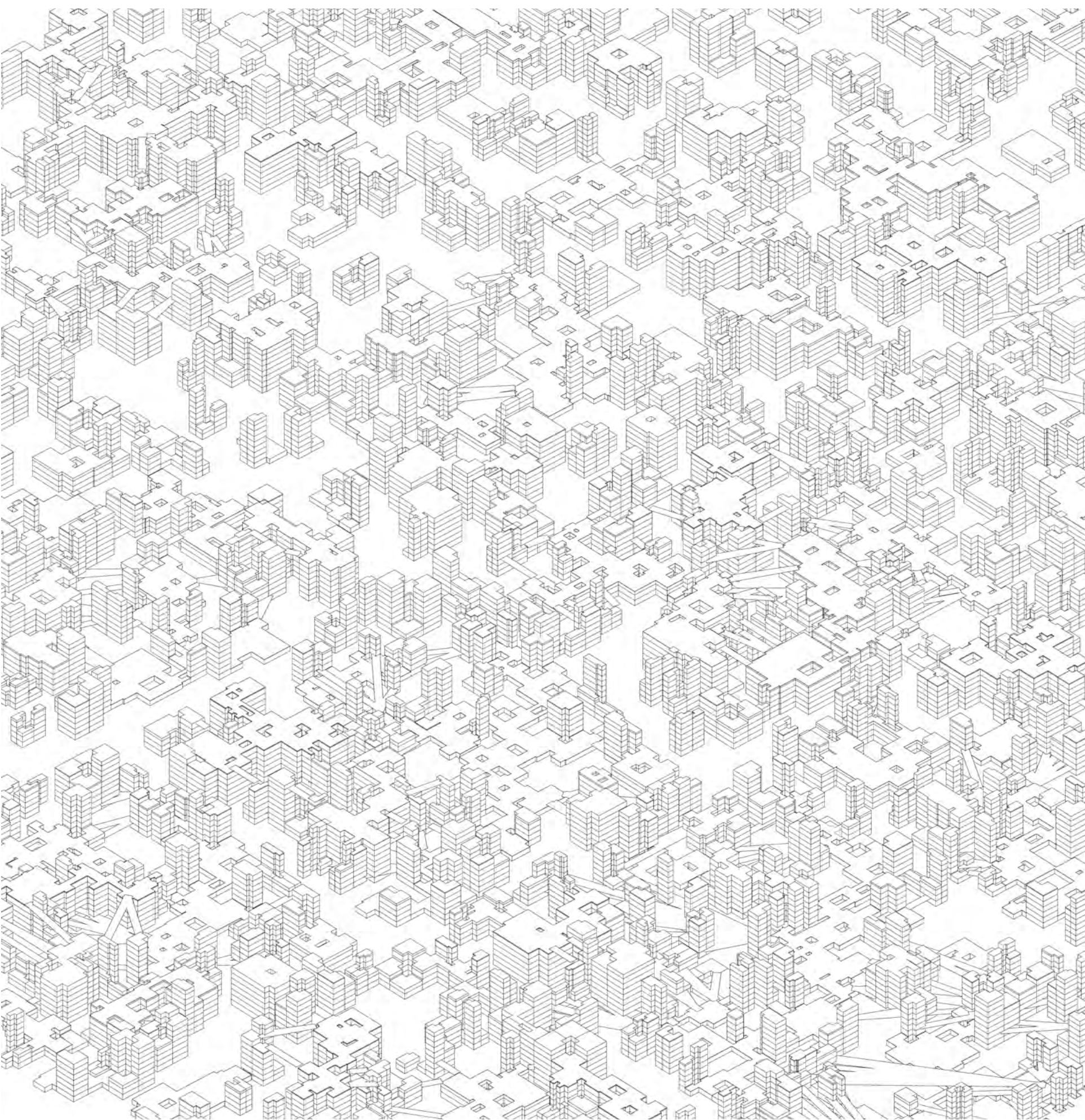


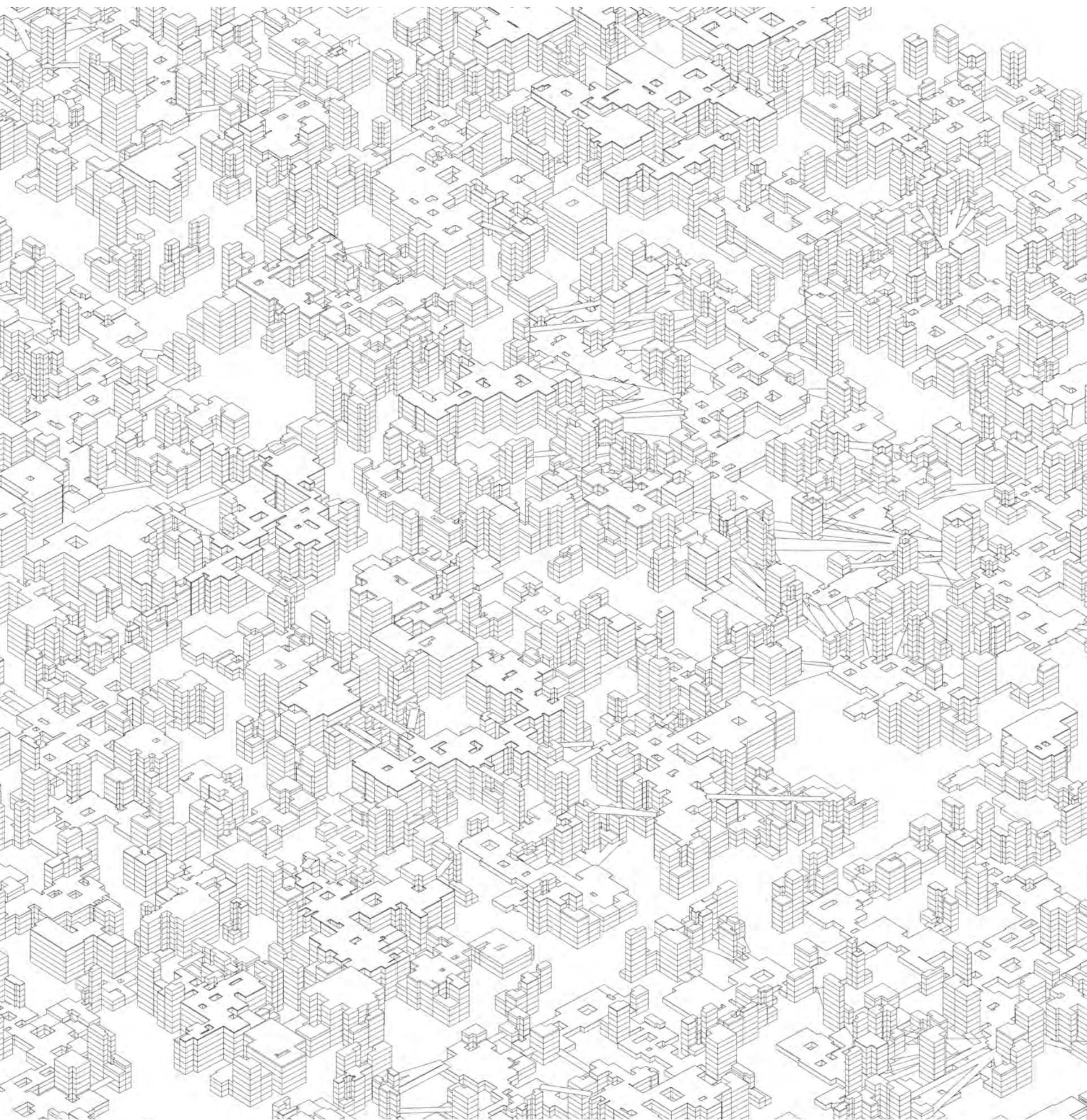




Urban Variation Through Evolutionary Development

Evolutionary Processes in Design and the Impact of Multi-Objective
Evolutionary Algorithms Generating Urban Form





5.3.4. Analysis

Due to increasing the phenotype's size and the multiple geometric operations and analyses incorporated within the simulation, the evaluation time per solution was recorded at approximately 6 seconds, in which the total simulation runtime was recorded at approximately 42 hours (in all experiments conducted in this research, a consumer grade laptop was the primary computational platform). Although the simulation runtime is almost double the previous experiment, there was no risk in the simulation 'crashing' as only the genomes of the phenotypes were recorded rather than their geometric expression.

The first analysis performed was to ensure for a unified understanding across the entirety of the simulation run, therefore every 100th generation was selected for visualisation and evaluation in an attempt to observe the diversity of solutions within generations and their evolution across the simulation (figures 5.20. to 5.30.). The variation and convergence of solutions in each of the selected generations is evaluated by means of their Normal Distribution (and the comparison of the generation's normal distribution across the entire simulation) and the distribution of the pareto front solutions (the solutions that are not pareto dominated by any other solution).

With regards to the normal distribution, the standard deviation factor for each criterion is calculated, with the presented generation's normal distribution curve highlighted. For the first criteria (increasing distance between public spaces), the simulation evolved solutions with greater fitness yet maintained an adequate level of variation across the population. The second criteria however (increasing the areas of neighbouring open spaces), the algorithm maintained variation yet could not evolve towards any considerable increase in fitness. As for the third criteria (decrease solar exposure on street level), the simulation increased the fitness of solutions, however there were a few instances of high convergence among population. Finally, criteria four (increase area of upper level open spaces) had the greatest fluctuation among the four criteria, with a constant back and forth between variation and convergence throughout the entirety of the simulation run (figure 5.31.). Moreover, the fittest solution for each objective throughout the population was selected through which the morphology is presented and its location in the population is highlighted (figures 5.32. to 5.35.) ([Animation 4a](#)).

With regards to the pareto optimal front, the distribution of solutions was somewhat uniform throughout the simulation, emphasizing the conflict between the criteria and the inability for any one criterion to drive the simulation more than the others. It must be noted however that although each generation produced 25 phenotypes, a small selection of these phenotypes were considered to be 'errors' (or anomalies, similar to the previous experiment) (figure 5.42), this was a result of the algorithm's failure to compute some of the phenotypes, thus unable to provide fitness values for these 'error' solutions. Therefore, these solutions were culled from the analyses and do not influence the results.



In addition to the analysis of solutions at the generation level, 5 solutions were selected amongst the 25,000 individuals through the ranking of the population according to the global fitness rank (extracted through the parallel coordinate plot). Each solution selected was analysed and compared to the remainder of the population, and a detailed view of the morphological properties of each solution is presented (Figure 19). The selected phenotypes highlight the simulation's ability to evolve a highly integral morphological distribution of ground level and upper level public space, connected skyways and a variation in the distribution of density throughout the superblock (figures 5.36. to 5.41.).

5.3.5. Conclusions

The experiment conducted evolved a population comprised from 25,000 solutions, in which 1000 generations were evolved each made up from 25 individuals. More importantly, the experiment is the first to use a superblock comprised from 100 blocks, thus expanding and highlighting the relationship between the blocks to a greater degree than in previous experiments. Where experiment 3 incorporated within it a fitness objective that aimed to drive the superblock away from the grid-like linearity between its blocks, the superblocks evolved in experiment 4 achieved this without the necessity of incorporating a specific fitness objective that optimised against linearity. This was primarily due to the regulation between the genes and fitness objectives, but more importantly, the division of the body plan of the phenotype. The non-linearity between blocks within the superblock extended to the upper level connections, in which they 'broke free' from the grid like distribution that was inherent in the original primitive ([Animation 4b](#)). Finally, although the simulation run time far exceeded the previous experiments, the actual computational load was minimal; this allowed the simulation to run 1000 generations (or more if

required) without the computational platform crashing. This was primarily due to the shift in how the superblock was constructed in the design problem, in which the focus was predominantly on the 2d representation of the phenotype rather than the 3d representation.

The applied selection method of the 'global rank' favoured a set of solutions that shared very similar properties, indicating that although the simulation optimised for the four criteria independently, combining each solution's global rank proved to be an inefficient method to extract diverse solutions from the population. This emphasises the necessity to adapt the analytical and selection methods applied to the results evolved by the simulation in response to the design problem developed. Where one selection approach was beneficial in extracting diversity from the population for one experiment (such as experiment 2), this may not be the case for an alternative one (experiment 4). Nonetheless, selecting a single solution (or group of solutions) for a multi-objective problem comprised from conflicting criteria while attempting to limit the user's preference is a challenging task. Although ranking the solutions according to their fitness rank or relative fitness difference may assist the user in resolving this issue, it is highly dependent on the fitness objectives running the simulation. Therefore, the formulation and reformulation of the design problem is key to address this.

The experiments conducted have examined and demonstrated the significance of the analysis of the simulation's output in the reformulation of the design problem in order to direct the levels of variation generated by the simulation. The following and final experiment examines the above through conducting the analysis of the solutions *within* the simulation and using the results to *dynamically* direct variation between generations throughout the population.

5.4. Experiment 5 - Controlled Morphological Variation

5.4.1. Ambition

Through all experiments conducted thus far, variation was achieved through the external analysis of the simulation's output towards the formulation of the design problem, and although the methods and tools developed have made this process as streamlined as possible, the feedback loop between the output's analysis and the reformulation of the design problem sits outside the loop of the evolutionary algorithm. In this context, and with the objective of directly controlling variation internally to the simulation, the following final experiment examines the benefits of incorporating a population-based fitness criterion as a fitness objective to direct the diversity of solutions 'live' within the algorithmic run. The objective is to dynamically control the degree of variation and convergence achieved within the population; one that is informed through properties internal to the simulation itself.

The experiments conducted have demonstrated that the control over variation within the population becomes more challenging as the design problem becomes more complex, this is primarily due to the design problem being associated with a complex fitness landscape. The complexity of the landscape decreases the chances of the simulation from finding a global optimum; however more importantly, it also increases dramatically the risk of the simulation generating a solution set that is restricted to a local optimum. In this context, the following experiment examines an alternative approach to the navigation of the fitness landscape through utilising a population-based fitness criterion as a secondary unit of control that directs the balance between exploration and exploitation of individuals dynamically within the algorithmic loop.

5.4.1.1. Fitness Landscapes

The complexity of an optimisation problem is represented through the problem's fitness landscape, i.e. the distribution of solutions (according to their fitness values) in relation to one another. It is the fitness landscape that the optimisation algorithm will navigate in the aim of locating optimal (or near optimal) solutions. In its purest and simplest form, the fitness landscape is represented as a single continuous curve, where all the possible solutions are distributed across this curve. The fittest solutions are located on peaks (i.e. high points on the curve), while weak or unfit solutions are positioned in valleys (i.e. low points on the curve) (this distribution is if the problem was maximising the fitness function, if minimising the fitness function, then the distribution of solutions would be inversed) (figure 5.43.). As the problems becomes more complex, so does the shape of the fitness landscape (Luke, 2013).

The complexity of the fitness landscape holds a direct impact on the success or ease in which the optimisation algorithm is able to locate fit solutions in the population, as a very complex optimisation problem will challenge the algorithm in locating peaks across the fitness landscape, and thus may result in the algorithm prematurely converging towards a localised peak, or endlessly exploring the fitness landscape without converging at all. One of the implications of the experiments presented throughout the research was that by focusing on the processes at either end of the evolutionary simulation, the aim was to simplify the optimisation problem's fitness landscape by maximising the efficiency of the design problem through an efficient formulation and relationship between the objectives, genes and body parts of the design problem, as well as a thorough analysis of the results outputted by the simulation. However, despite the above, the fitness landscape (i.e. the complexity of the design problem) may still challenge the evolutionary simulation in converging to (or at times diverging from) a specific solution set. As such, introducing a fitness measure that directs the simulation towards converging or diverging 'live' within the optimisation process would serve as an additional tool that would facilitate a 'directed' navigation of the fitness landscape in favour of a fitness objective driving the simulation.

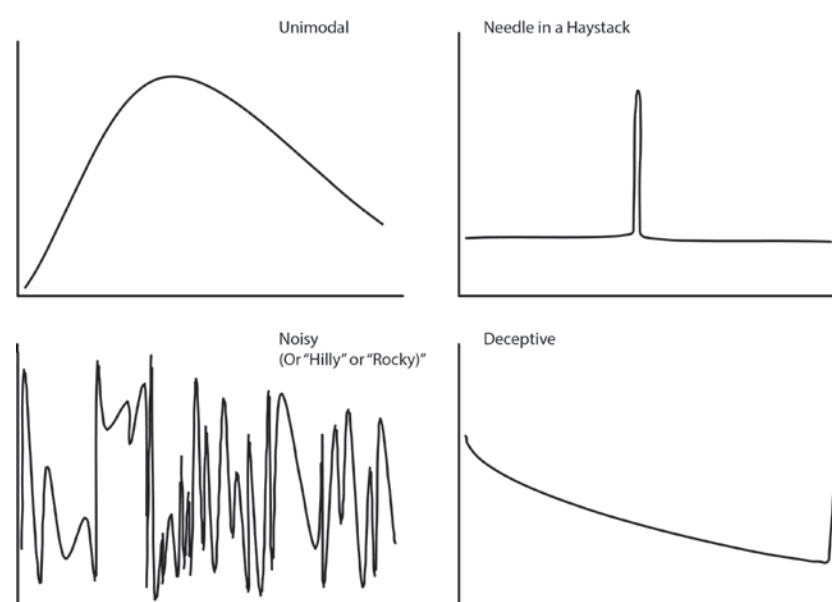


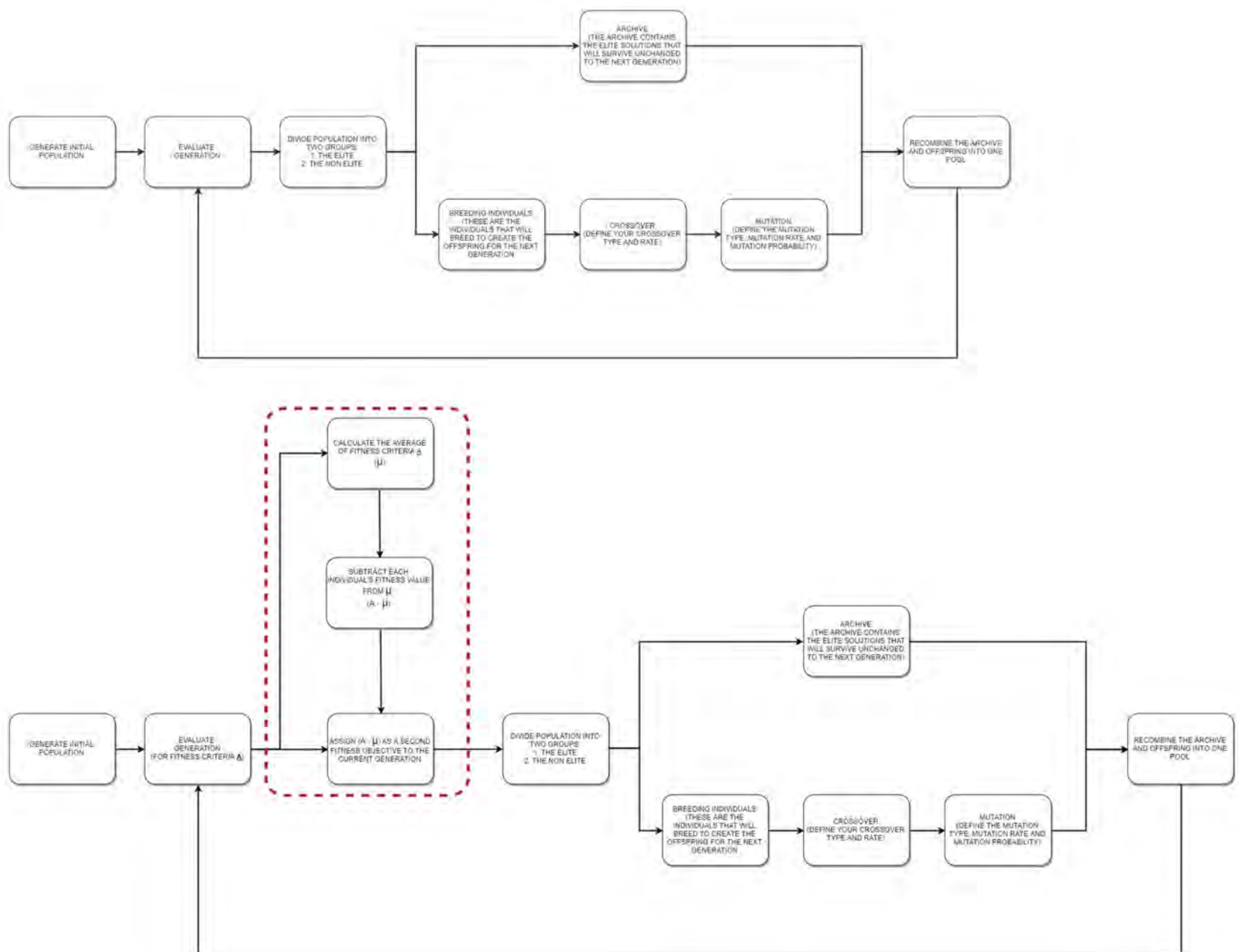
Figure 5.43.
Examples of different types
of fitness landscapes (Weise,
2009)

5.4.1.2. Population Based Fitness Criteria

To control variation amongst the population, the differences in fitness values between all individuals within a single generation needs to be calculated. The challenge arises by the fact that this calculation must occur iteratively at the end of each generation, with the resulting value to be attributed to each solution in the generation and utilised as a fitness criterion to evolve subsequent generations. A multi objective approach is needed due to the population-based fitness criterion being utilised as an additional fitness objective. Initial attempts to incorporate the population-based fitness criteria were carried out through the solver *Octopus*; however, as the algorithm's loop process within *Octopus* could not be interrupted, the software '*Octopus.explicit*' - a variation of *Octopus* developed by the same author - was utilised as an alternative, which allows the user to interrupt the algorithm's workflow and make adjustments as required (figure 5.44.).

When calculating the population-based fitness criterion, the resulting fitness values must present two critical properties: a) The value must be derived from all the individuals within a generation, and b) it had to be a value that would be unique to each solution. Although the standard deviation value of each generation reflects the degree of variation between solutions, the value calculated is a single value, one that was not unique to each individual. To bypass this issue, the deviation of each individual's fitness value from the population average was calculated and attributed to each individual uniquely. Although this indicates the level of variance within the population, it also allows for two solutions with different fitness values that are equidistant from either side of the population average to have the same population-based fitness value, thus driving the algorithm to minimise (or maximise) variance levels by reducing (or increasing) each solution's distance to the average in both its positive *and* negative. An increase in this population-based fitness criterion throughout the simulation translates to greater deviations between each individual and the generation average, meaning greater variation among solutions. In contrast, a decrease in this value conveys lower deviation of individuals to the average thus translating to lower diversity among solutions. The objective is to increase/decrease the population-based fitness criterion while simultaneously optimizing for the fitness objective used to calculate it.

Within the algorithmic loop, the population based fitness criteria and its calculation is introduced at the beginning of each iteration; specifically, after the solutions of the preceding generation have been evaluated, and before they are selected for reproduction and mutation. The aim is to ensure that the added fitness measure is calculated according to the results of the latest generation thus ensuring it is considered when evaluating solutions to be selected for the following generation. This occurs within every iteration of the optimisation process.



5.44.
Comparison between the
original Octopus.e algorithmic
workflow (top) to the modified
workflow (highlighted in red in
the bottom image).

5.4.2. Experiment Setup

The computational setup for the design experiments presented have been developed according to the complexity of the problem being investigated. The goal of the presented experiments is the analysis and examination of the effects of incorporating a population-based fitness criterion on the morphological variation within a population. Therefore, the experiments were designed to ensure a full understanding of their results. Experiment 5A builds on the previous experiments through investigating the morphological variation of phenotypes within the context of an urban superblock; therefore, the output from experiment 4 was carried forward into the initial population of experiment 5A.

In contrast, and in response to the complexity of the problem, experiment 5B utilised a highly simplified phenotype as the base primitive (which is explained in the following sections), this was in response to the complex fitness landscapes that accompany multi objective problems. However, both experiments shared the same simulation parameters; a mutation rate of 50%, mutation probability of 20%, a crossover rate of 80% and an elitism size of 50%. Finally, the population size for both experiments was set to be comprised from a generation size of 20 solutions and a generation count of 50.

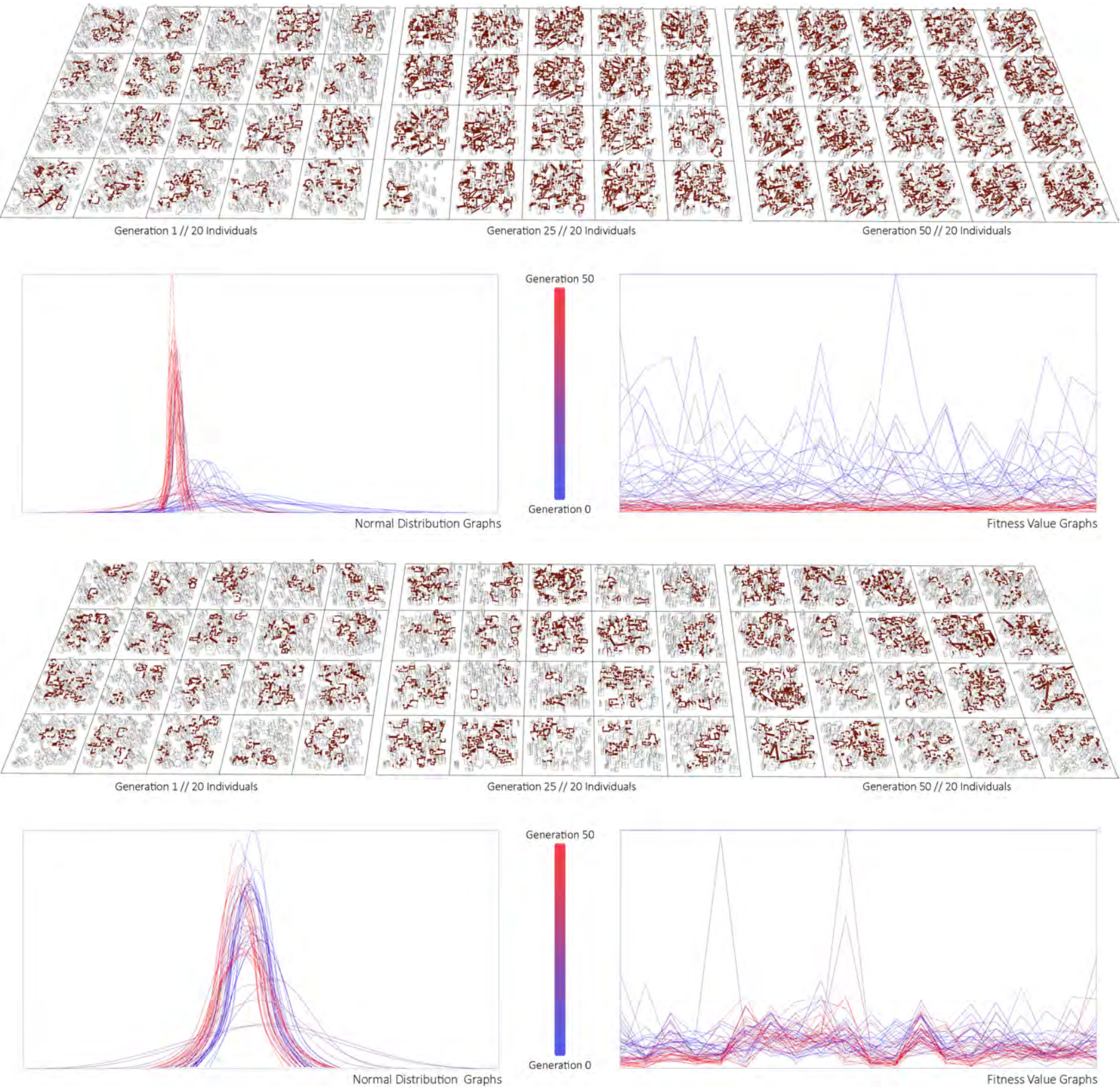
5.4.3. Experiment 5A – Dynamic Variation for a Single Objective

Within the first experiment, the population-based fitness criterion is applied to a single objective problem while experiment 5B (presented in the following section) applies it to a multiple objective problem.

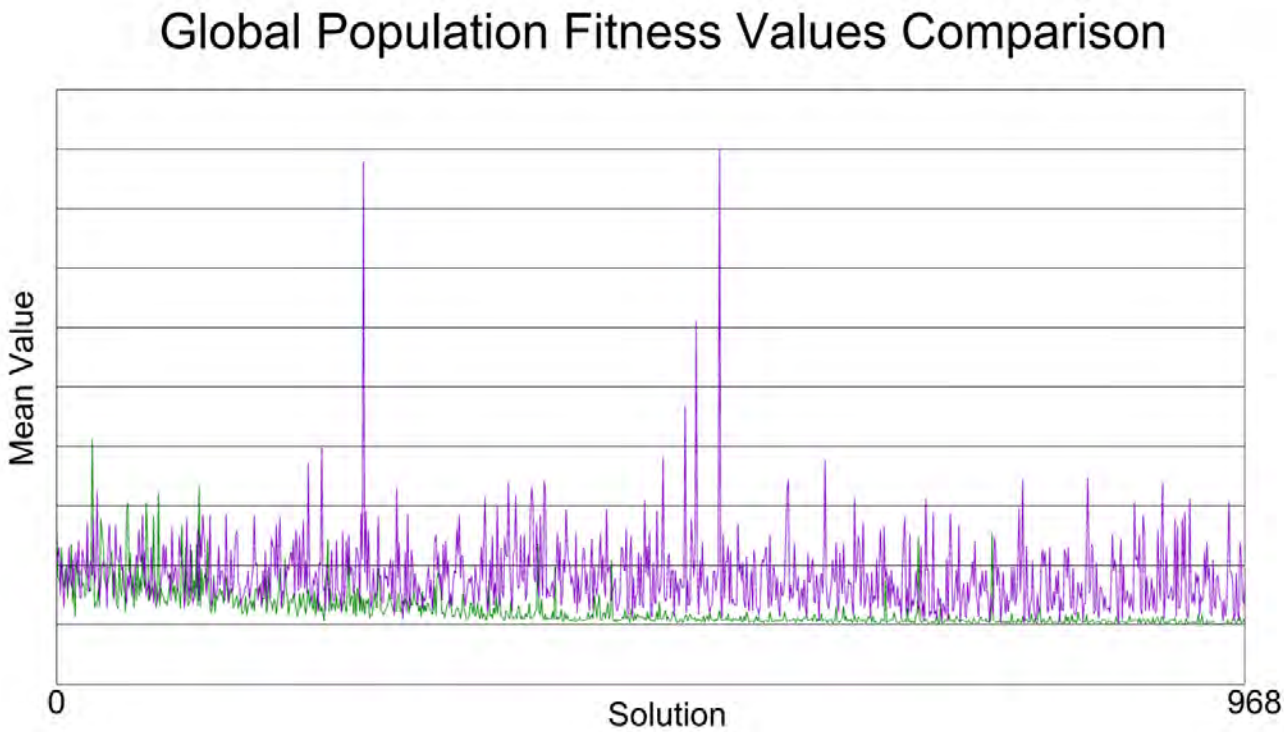
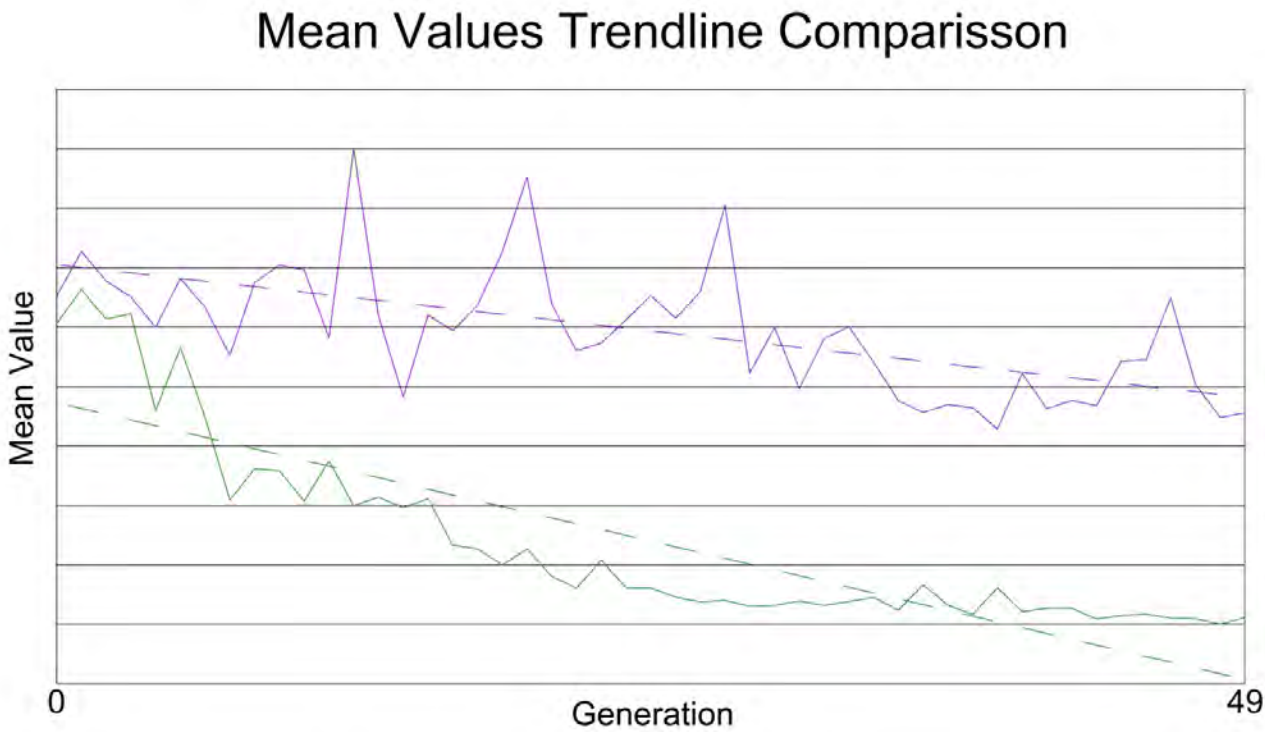
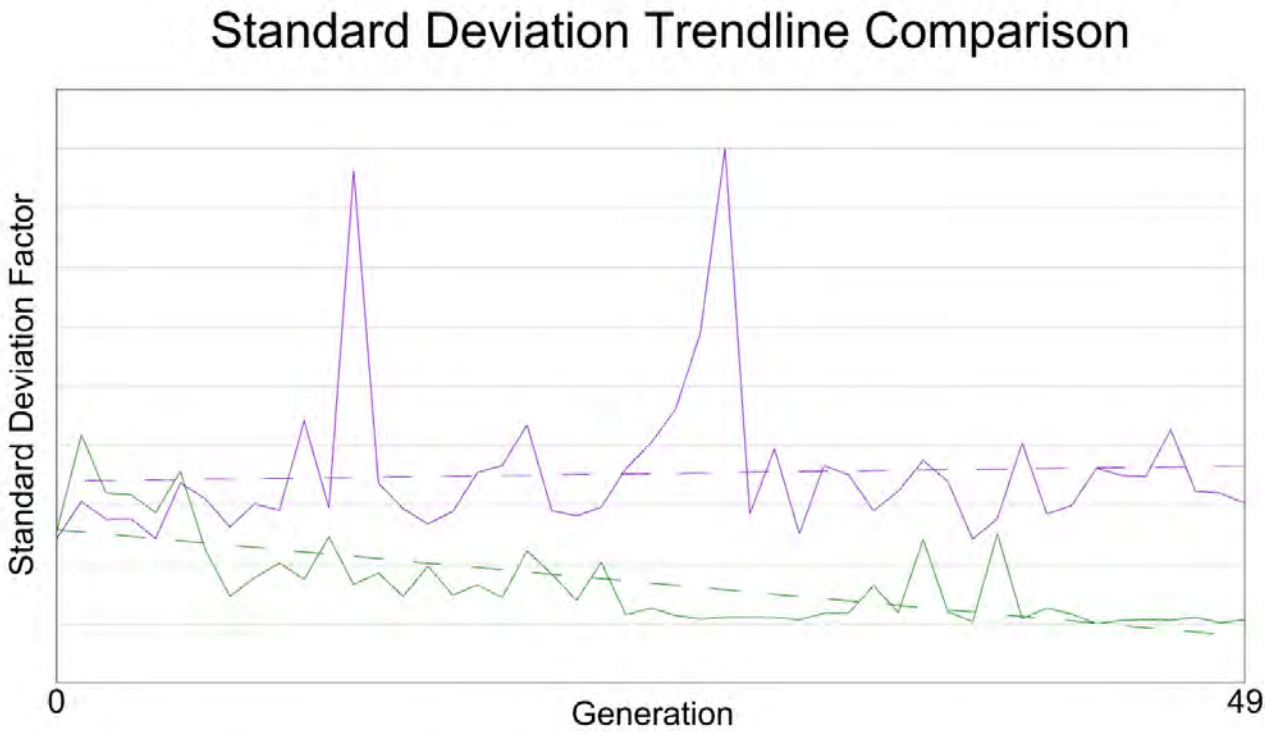
The primitive phenotype for the first experiment is the urban superblock applied in Experiment 4 in the previous section; the Fes superblock. The same genes (variables) and body plan (geometric composition of the phenotype) used in the experiment setup of experiment 4 were maintained, however in to simplify the design problem so as to better understand the impact of implementing a population based fitness criterion to the evolutionary simulation, only one of the fitness objectives were selected to be optimised. In this case, the objective to maximise the floor areas and connections of all upper level space was being optimised for in the experiments conducted in experiment 5A. Additionally, the size of the superblock was also maintained.

The aim of the experiment is to first run a 'benchmark' of the simulation without the use of the population based fitness criteria, followed by re-running the exact same experiment, i.e. maintaining all of the same properties of the first experiment, with the only difference being the introduction of the new fitness measure that will aim to calculate the distance of each solution generated within the population from the population average and increase this distance within every added iteration. The results of the second experiments are then extracted and compared to the results of the first 'benchmark' experiment.

5.4.3.1. Outcome



5.45. Comparison of the output of Experiment 5A. The image on top presents the experiment conducted without the population-based fitness criterion while the image on the bottom presents the output of the experiment with the population-based fitness criterion.



5.46.
The comparison between the standard deviation and mean values for the results of the experiments both before and after the implementation of the PBFC.

■ Results without the PBFC
■ Results with the PBFC

5.4.3.2. Analysis

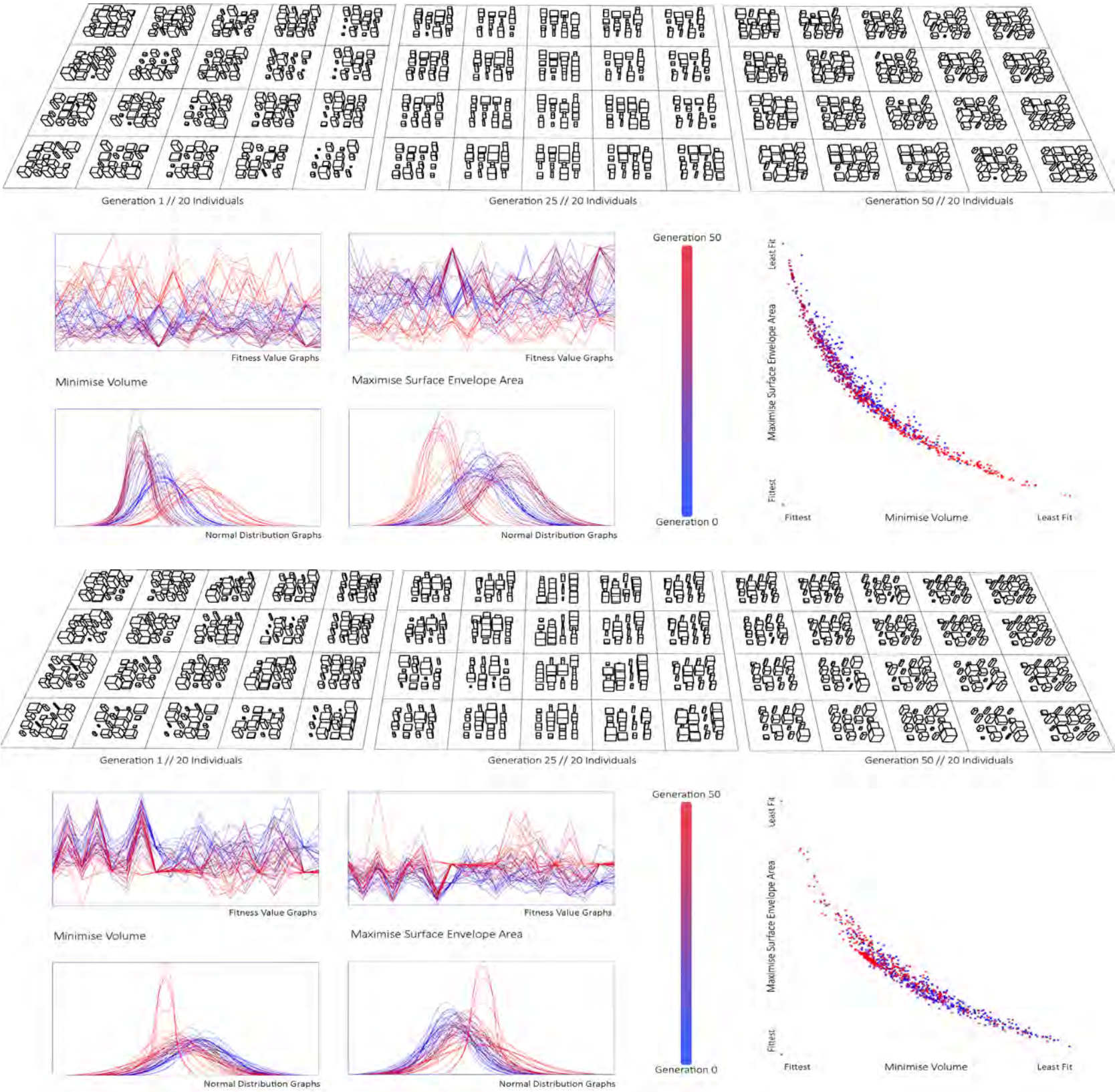
As previously stated, the conducted experiments are carried out as a two-step process; firstly, the simulation ran without the population-based fitness criterion, in essence the algorithm was simply attempting to increase the area of upper level spaces without any restrictions; as expected, this resulted in a solution set that quickly converged to phenotypes that had maximised upper level areas. Although unsurprising, this was necessary for a comparative analysis to the second step of this two-step process. Step 2 ran the exact same experiment as step 1, with the only difference being that the population-based fitness criterion was introduced, and the simulation was required to increase its value; in an attempt to reduce convergence and maintain a degree of variation among the population. The comparisons between the normal distribution curves and their respective standard deviation values as well as the generation mean values, in addition to the generated phenotypic morphologies, present promising results (figure 5.45. and figure 5.46.) ([Animation 5](#)).

The utilisation of the population-based fitness criterion as a fitness objective allowed the simulation to maintain a higher degree of variation between solutions; more importantly however, the fitness levels of the generations throughout the simulation continued to incrementally increase. The results present that a population-based fitness criterion, that is derived from the values of an objective of which the algorithm is optimising for, has been able to maintain an adequate level of variation without limiting optimisation. This is examined further in the following section.

5.4.4. Experiment 5B – Dynamic Variation for Multiple Objectives

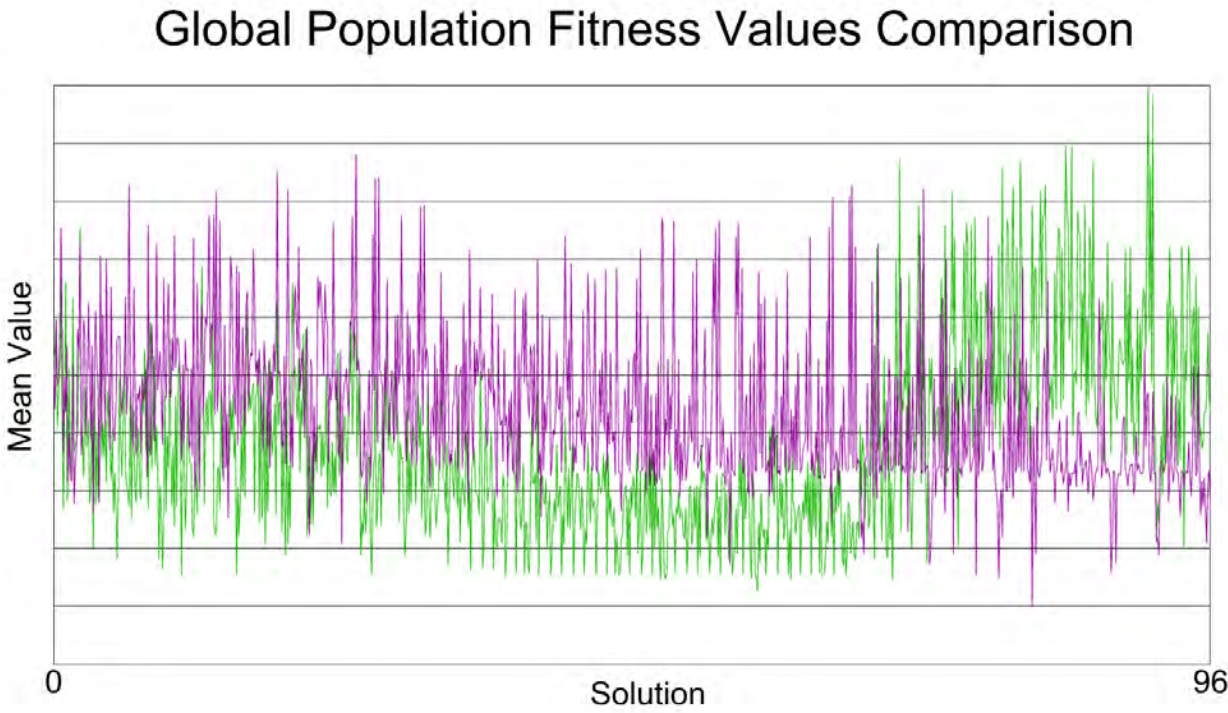
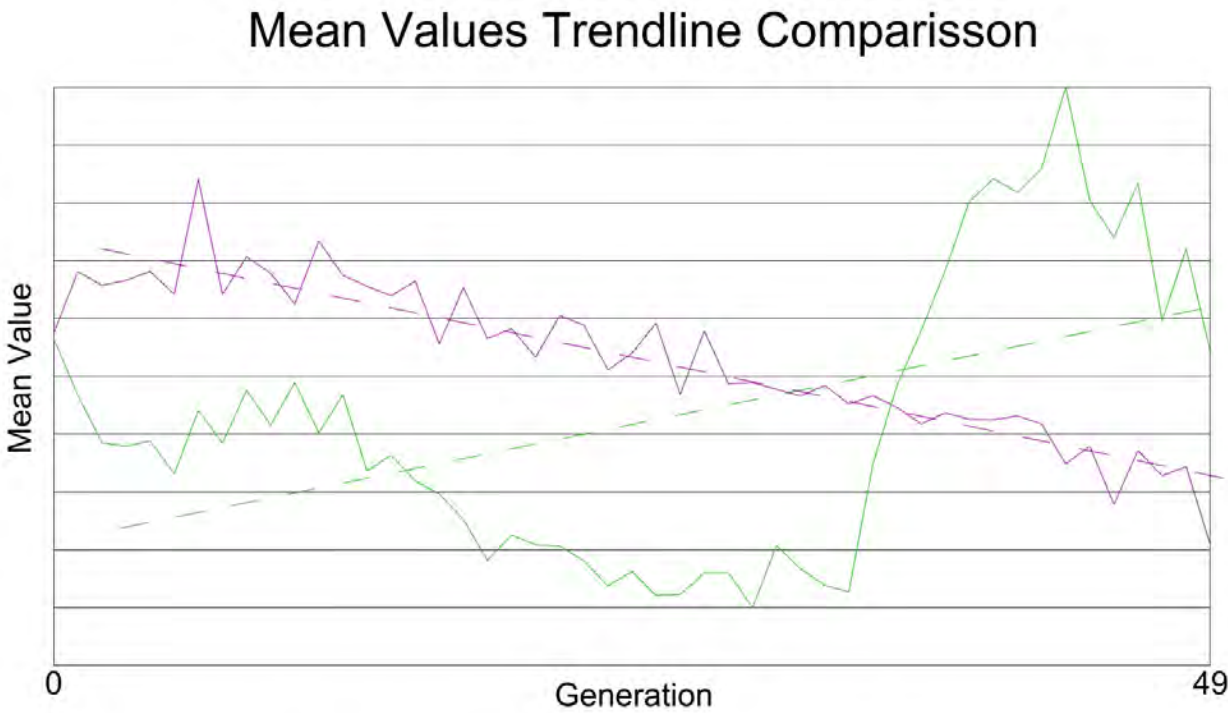
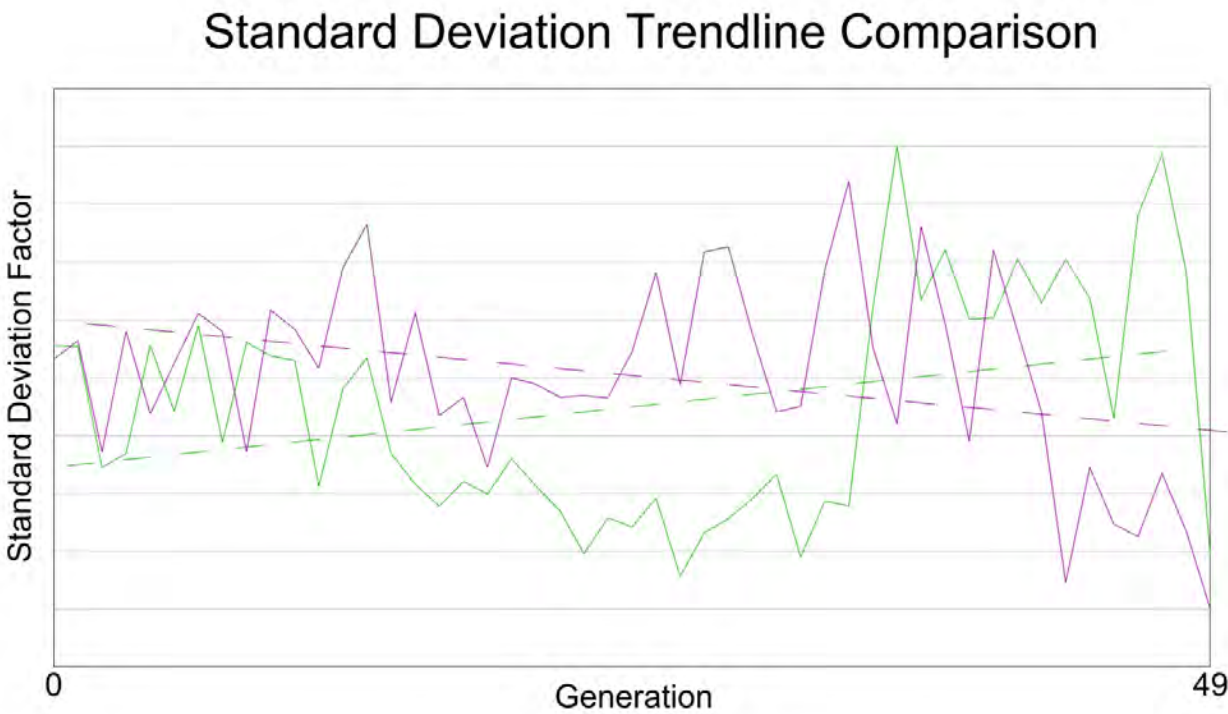
Applying the population-based fitness criterion on a problem with multiple objectives becomes significantly more challenging. The difficulty does not arise from its application, but from its analysis. Multiple objectives (and their effects on the simulation) require a highly simplistic problem in order to comprehensively examine and assess the effects of incorporating the population-based fitness criterion within the algorithm. This is due to the fact that a complex problem increases the complexity of the fitness landscape dramatically, adding multiple additional variables that may affect the balance between exploration and exploitation of solutions throughout the simulation; thus, the analysis of the effects of the population-based fitness criterion becomes more difficult to discern as multiple other factors are involved in the variation and/or convergence of the population. Therefore, rather than relying on the primitive utilized in experiment 5A (the urban superblock of the city Fez); experiment 5B employed a simplified primitive derived from a 4x4 grid of blocks. The objectives defined for the simulation were the following; the algorithm will minimise the volume of the solutions while simultaneously maximise their surface envelope area - 2 criteria that are in clear conflict.

5.4.4.1. Outcome



5.47. Comparison of the output of Experiment 5B. The image on top presents the experiment conducted without the population-based fitness criterion while the image on the bottom presents the output of the experiment with the population-based fitness criterion.

Fitness Objective 1 - Minimise Volume

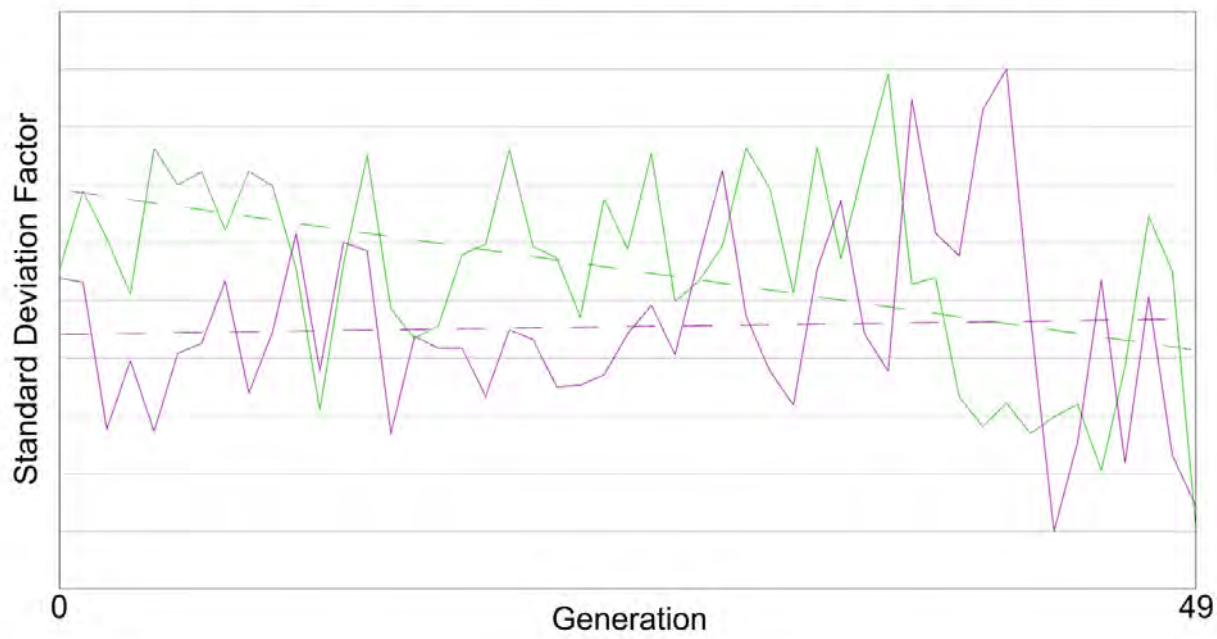


5.48.
The comparison between the standard deviation and mean values for the results of the experiments both before and after the implementation of the PBFC for Objective 1

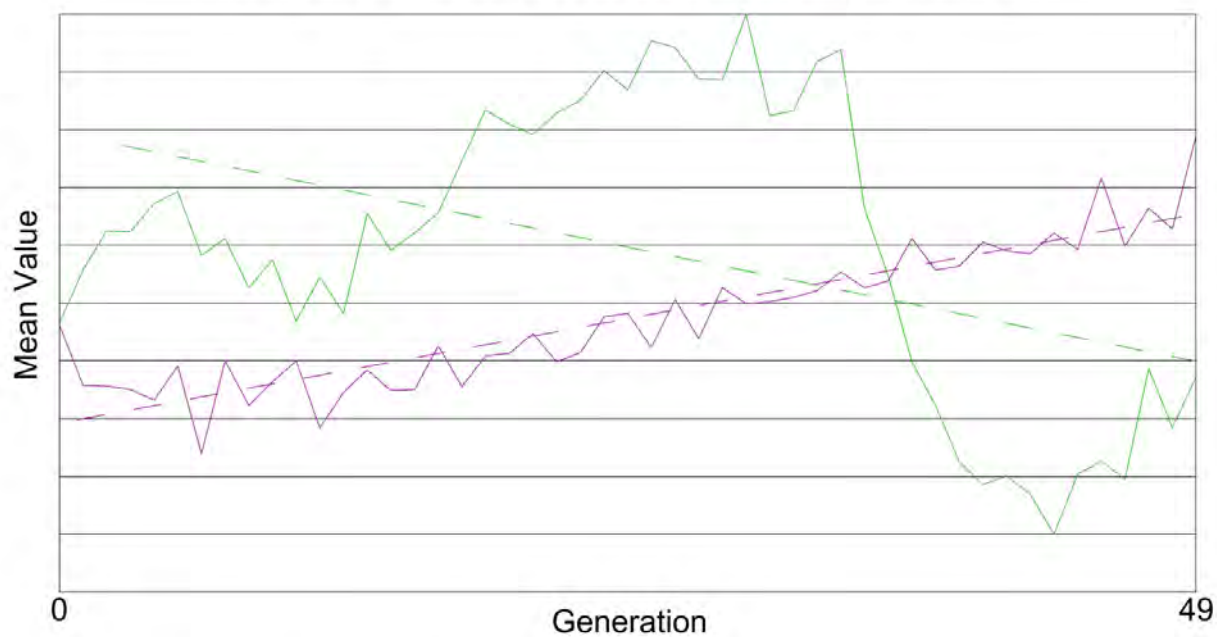
Results without the PBFC
Results with the PBFC

Fitness Objective 2 - Maximise Surface Envelope

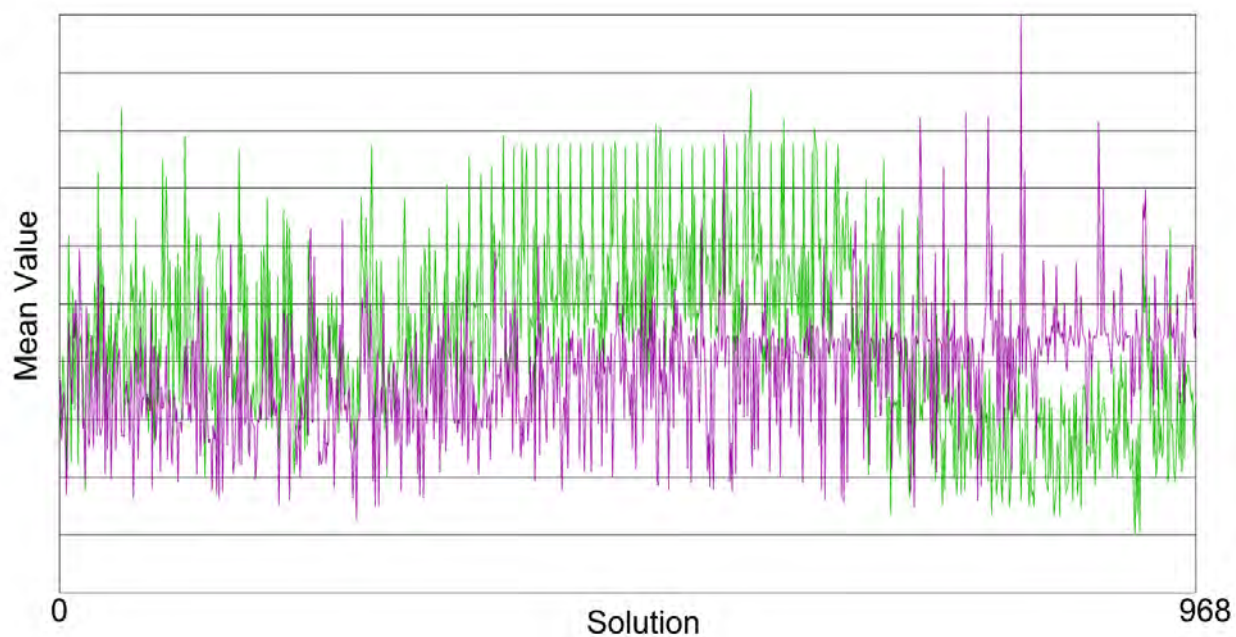
Standard Deviation Trendline Comparison



Mean Values Trendline Comparison



Global Population Fitness Values Comparison



5.49.
The comparison between the standard deviation and mean values for the results of the experiments both before and after the implementation of the PBFC for Objective 2.

■ Results without the PBFC
■ Results with the PBFC

5.4.4.2. Analysis

As with experiment 5A, experiment 5B was carried out as a two-step process. Step 1 ran the simulation without the incorporation of the population-based fitness criterion; the result was typical to a multi-objective problem with conflicting criteria; the Pareto front distribution was concave implying that as the solution's fitness value for one objective was optimised, this resulted in the decrease in fitness of the second objective. This is also visible through the normal distribution graphs for the two criteria, as they are inversely proportional to one another. However, what was unexpected (and unintentional) was that one criterion was favoured over the other, in this case, maximising the surface envelope area was awarded more weight by the algorithm over minimising the total volume. This was observed multiple times in the experiments conducted in this research; despite the original formulation of the design problem aiming for a balanced weighting between the fitness criteria, the solver would at times favour one criteria over the other.

In step 2 of the experiment, the population-based fitness criterion was derived from the volume fitness objective value, therefore the algorithm setup attempted to maximise surface envelope area, minimise total volume area and minimise the variation of individuals with regards to their volume; by doing so, the ambition was to drive the experiment towards awarding greater weight in minimising the volume of solutions in an attempt to counteract the dominance displayed by the surface envelope area criterion that was exhibited in the first step of the experiment. Experiment 5B demonstrates that through applying the population-based fitness criterion and minimising its value, the simulation favoured optimising the volume criterion over the surface area criterion. This is evident when comparing the normal distribution graphs and standard deviation factors of the populations between these two experiments, as well as the distribution of solutions in the objective space and the resulting phenotype morphologies (figures 5.47., 5.48., 5.49.) ([Animation 6](#)).

5.4.5. Conclusions

The experiments conducted aimed to control the morphological variation of solutions within the population by incorporating the analytic toolset within the algorithmic loop, as opposed to external to it. In doing so, the reformulation of the design problem was carried out dynamically within the evolutionary simulation. In both experiments 5A and 5B, a 'reference' experiment was conducted so as to compare and analyse the results of utilising the population-based fitness criterion on the variation levels generated by the simulation. In Experiment 5A, the design problem was formulated as a single objective problem, one that optimised relatively quickly towards the global optimum. However, through the introduction of the population-based fitness criterion, the experiment was successful in maintaining variation within the population while simultaneously optimising towards global optima.

On the other hand, the design problem for experiment 5B was formulated as a multi-objective problem. In the 'reference' experiment conducted (the experiment without the incorporation

of the population-based fitness criterion), a behaviour that was observed in experiment 2 (the Barcelona superblock presented in chapter 4.3) re-emerged, in which although the design problem was formulated with the intent to give equal weighting to the conflicting fitness objectives, the evolutionary simulation evolved solutions that optimised for one objective quicker than the other. Interestingly, through incorporating the population-based fitness criterion, the design problem was reformulated by the simulation to counteract the uneven weighting between fitness objectives observed in the reference experiment.

The significance of the results observed in experiments 5A and 5B, is that through dynamically controlling variation within the evolutionary solver, the simulation was capable of maintaining variation while continuing to optimise the population, as well as counteract instances in the simulation that optimised for one objective quicker than the other. In the context of the experiments conducted throughout this chapter, the developed method can be utilized to drive the evolutionary simulation towards maintaining an equal optimisation between fitness objectives. An example of this would be for its application in experiment 3, in which three of the fitness criteria directed the simulation away from optimising for the fourth criteria. This ensures that greater control is maintained on the output of the evolutionary simulation, *without* the necessity to modify the evolutionary algorithm itself. This demonstrates the practicality of utilising a population-based fitness criterion within an adaptable model that can be utilised across a range of different design problems.

The application of a population-based fitness criterion as a mechanism to control variation can be further improved; one approach is through utilising it as a regulatory mechanism, in which it can be turned on or off (expressed or suppressed) within the evolutionary simulation in response to variation thresholds imposed within the design problem (for example if insufficient morphological variation is generated by the simulation, the population-based fitness criterion would be 'expressed' to increase variation between solutions within the population). Additionally, at its current state, solutions located on either side of the average are given the same population-based fitness value, which drives the algorithm to minimise (or maximise) the distance between the solutions on both sides of the average; however, there is an opportunity to drive the population towards increased (or decreased) average levels by minimising (or maximising) the distance between solutions on only one side of the average, thus allowing for added weight to be applied to solutions with greater (or lower) fitness values.

5.5. Summary and Reflections

The morphological variation of urban form and its response to different environmental and climatic conditions is approached through the application of a biological evolutionary model that utilises the urban superblock as the primitive geometry to which transformations are applied to and consequently analysed for selection. The significance of the statistical analysis of the numerical data generated by the evolutionary simulation is critical to the efficient formulation and reformulation of the design problem, one that is expressed towards generating a population of solutions that is both diverse and optimised. Additionally, the role of regulating between the genes, body parts and fitness objectives, and the methods in which this is applied, in the design problem is as equally important for generating morphological variation of urban form.

Experiment 1 applied the regulation between genes, body parts and fitness objectives within two design problems. Both problems were formulated and expressed in the same way, with the only difference being is the first (experiment 1A) was within the framework of a single objective problem, while the second (experiment 1B) was within the framework of a multi-objective problem. The comparative analysis of the two experiments demonstrated the significant differences in morphological variation achieved through the two different approaches. The objective of this analysis was to highlight the impact of regulatory mechanisms in generating morphological variation, and how this is significantly limited if approached through a design problem formulated within the framework of a single objective.

Experiment 2 reformulated the design problem developed in experiment 1B by modifying the genes, body parts and fitness objectives, in addition to increasing the population size from 500 solutions to 10,000 solutions. In doing so, the experiment highlighted the significance of statistical analysis over visual analysis of the simulation's output. The experiment applied many of the analytic tools developed in chapter 3, and examined the relationship between the population size and the algorithmic parameters driving the evolutionary solver, and the impact that this relationship has on the simulation's navigation of the fitness landscape. Additionally, the experiment developed methods that increased the efficiency (by reducing the computational time) of the solar analysis conducted within the design problem through an alternative approach of mesh subdivision of the phenotypes' geometry.

Experiments 3 carried forward the methods and tools developed in experiments 1 and 2, and applied them to generate variation of urban superblocks within an urban tissue located in an extreme climate. The design problem was formulated through utilising the Microrayon, the typical soviet block, located in the planned city of Norilsk in the Siberian arctic. Experiment 3 increased the population size generated by the simulation to 26,000 solutions, which was achieved through evolving 260 generations with 100 solutions each. The formulation of the design problem aimed at evolving solutions that broke the linearity inherent to the urban superblock by allowing each block to move and rotate. Through this approach, the evolutionary simulation was successful in evolving solutions that broke this linearity, but more importantly, achieved it through driving the population towards abandoning one of the body parts that comprised the phenotype, the tower block.

Experiment 4 applied the methods developed in experiment 1 through 3 to generate urban variation of a superblock located in an in an opposing extreme climate to the one selected in experiment 3; the evolved city of Fes El Bali located in the north of Africa. Through this experiment, the design problem was reformulated towards one that signified the 2dimensional representation of the phenotype over the 3dmionesional representation. In doing so, the body parts that comprised the phenotype were primarily 2dimensional, which required that their regulation by the genes and fitness objectives to be applied earlier in the design problem rather than towards the end. This minimised the computational load significantly, thus allowing for the superblock to be comprised from 100 blocks as opposed to the 16-block superblock utilised in the previous experiments. Although the total population size in experiment 4 was similar to that in experiment 3, the method in which the it evolved was significantly different; in experiment 4, the generation size was comprised from 25 solutions, and the generation count was 1,000. This provided for a much greater frequency of iterations of the algorithmic run, in which the solver evaluated, selected and reproduced solutions more times than any of the previous experiments.

Finally, experiment 5 carried forward the evolved solutions from experiment 4 and aimed to gain a more dynamic control over variation within the population by utilising a 'population-based fitness criterion' within the algorithmic loop of the evolutionary simulation. This was achieved through analysing the variance value of each solution evolved by the simulation and incorporating this value as a fitness objective that can ultimately be used to either increase or decrease morphological variation within the evolutionary simulation. This approach was applied within the framework of a single objective problem (experiment 5A) and a multi-objective problem (experiment 5B), in which both experiments demonstrated a successful application of the population-based fitness criterion in directing morphological variation *dynamically* within the simulation.

The experiments conducted in chapters 4 and 5 have demonstrated that the primary challenge encountered through the application of an evolutionary process as a design tool is the ability for the simulation to maintain variation, between design solutions in the population, while simultaneously increasing in fitness for both the individual and the generation. This balance between exploration and exploitation forms the foundations for most (if not all) evolutionary algorithms; the difficulty of achieving this balance in the simulation is due to the tendency of either variation or optimisation to be favoured as the simulation progresses. In such cases, the generated population of candidate solutions has either converged very early in the simulation or has continued to maintain high levels of variation to which an optimal set could not be discerned; thus, providing the user with a solution set that has not evolved efficiently to the objectives outlined in the problem at hand.

Control over directing the degree of variation within the generation and among the population is thus critical, this is more so within design and in specific, urban design. The complexity associated with design problems driving urban development require an adaptable model that is capable of simultaneously addressing multiple conflicting environmental stresses within extreme climates

in the same simulation. In doing so, a population of solutions (not a single solution) is evolved that optimises for each objective locally, yet also impacts the population globally, through a regulation between the genes, body part and fitness objectives expressed in the design problem. In contrast to the traditional design process of perfecting a single unique design solution, the applied model employs a process of ‘evolving’ varied populations of context specific morphologies; allowing for greater variation of morphological attributes between different urban superblocks, thus moving away from the ‘universal city’ of the 20th century to one that is better equipped to the rapid environmental and climatic challenges of the 21st century.

The objective is to “delay” the designer’s influence over the final solutions until *after* they have been optimised for the criteria driving the design problem. Thus allowing the designer to make an informed decision on the selected solutions that is based on statistical analysis and emergent numerical patterns *in addition to* the visual analysis of the final geometries.

In this context, variation is *key*. More importantly, the methods that generate variation between solutions are pivotal to the evolutionary process. Therefore, the significance of the literature review, and the analysis of the intersection between the fields of evolutionary computation, evolutionary development and urban variation is critical in developing tools and methods that allowed for a more efficient approach to both generating *and* controlling variation within the applied evolutionary simulations. This was primarily driven by the analysis of principles of evolutionary development that highlight the role of regulation and regulatory mechanisms for generating morphological variation of evolved species, and the integration of such principles within the computational process. The experiments conducted aimed to demonstrate all of the above through the application of the developed model in design problems that varied in scale, complexity and formulation.

Conclusions

6.1. Introduction

The presented research aims to advance the role of evolutionary computation in design, and the different modes of its application for the development of multiple urban tissues that vary in scale, location and environmental and climatic conditions. Through incorporating evolutionary developmental principles within the formulation of the design problem, the conducted experiments aimed to address the issues of variation in the population-set and the means by which this can be both achieved and controlled. Moreover, the research highlights the necessary shift that is required from equating a design problem with a single 'optimal' design solution, to one that is addressed through a population of design solutions. In doing so, the population-based approach to solving design problems highlights the *populationist's* argument of evaluating each solution in the population according to its own unique traits; thus, avoiding the *typologist's* approach of defining a 'average' solution and attributing it as the most suitable for addressing the design problem (**Section 2.2.1**).

Additionally, the research highlights the significance of the numerical data associated with each solution outputted by the evolutionary simulation, and the comparative analysis between the complete data set of all the solutions in the population. Current approaches to the application of evolutionary simulations in design are heavily reliant on the final generation; and although the algorithmic setup of evolutionary principles aim to generate fitter solutions as the simulation progresses (for example through incorporating the archive within the algorithmic loop), the presented experiments demonstrate that this is seldom the case. Fitter solutions are found elsewhere in the population and not always in the final generation. Moreover, through this analytic approach, the experiments highlight different methods by which solutions can be ranked through selection criteria that analyse the different fitness values for each solution individually as well as collectively; thus, providing the user with alternative selection methods that serve either scenario of selecting a single solution or a set of solutions that address the design problem.

6.2. Research Questions

The research questions put forward in chapter 1 are restated below, accompanied with how the research addresses each question.

1. *Can the science of evolutionary developmental biology be implemented as a computational model to generate diverse and optimised morphological variation of urban blocks and superblocks?*

The study of evolutionary development, and specifically the role of regulatory mechanisms, in generating morphological variation between species through the use of an efficient genetic toolset was the primary driver for the formulation of each design experiment conducted. In contrast to the conventional approach of the application of evolutionary computation in design that focused more on the size of the gene pool, the experiments conducted incorporated regulatory

mechanisms between the genes, body parts and fitness objectives. This demanded a completely new approach to formulating the design problem, that required a careful analysis and setup of the phenotype's body plan, the genes (and gene sequences) that act on each body part, and how this relationship corresponds to the fitness objectives driving the simulation. As demonstrated through the experiments that differed in both scale and complexity; utilising regulation as an integral part of the expression and formulation of the design problem was critical in successfully generating morphological variation of the urban phenotype that was evolved through an efficient gene pool and a clear definition of the phenotype's morphological characteristics. Through this, the evolutionary simulation was capable of evolving a solution set that favoured specific body parts over others through changes in their expression between generations. More importantly, although the population optimised towards specific morphological traits globally, there was still within each generation sufficient variation between phenotypes that independently optimised for the different fitness objectives. However, the limitation was that the application of the regulatory mechanisms was primarily within the design problem, further research will examine its incorporation within the algorithm itself. Moreover, the analysis of the solutions was conducted on the morphology of each phenotype, however, there is a benefit for the analysis of how the body parts of each phenotype evolved throughout the simulation, thus providing an additional measure for demonstrating the success or failure of the regulatory mechanisms employed.

2. *Can a generative evolutionary model be applied to generate urban variation for evolving cities and planned cities located in two extreme climates?*

Sections 5.2 and 5.3 applied the developed tools and methods for generating urban variation of the superblock within two contrasting cities, Norilsk – a planned city, and Fes El Bali, an evolved city. In both cities, the experiments aimed to utilise the existing superblock and its morphological characteristics, and apply to it transformations that allowed it to diverge from the linear distribution of blocks within the superblock. In doing so, the evolved population set generated solutions that optimised for the fitness objectives for each urban tissue, in which significant variation was generated between solutions within the population that were unique in their optimisation for each objective. The aim of this was to highlight that through utilising the same urban phenotype, and by incorporating within it gene sequences (variables) that differed the phenotype's local and regional distribution and morphological definition, a solution set is evolved that holds within it sufficient variation of different superblocks that can be utilised in response to the different demands and stresses of the urban fabric's environment. The goal was to demonstrate the success of this approach in both planned and evolved cities, two urban models that will face equal stresses from a rapidly changing climate.

3. *Can an evolutionary model, operating across a range of scales, enable the development of urban superblocks that are evolved in response to stresses from their environment?*

The experiments conducted highlighted the significance of changing the scale of the urban phenotype. Where earlier experiments' phenotypes were comprised from a 16-block superblock, later experiments increased this number to a 100-block superblock. Additionally, the evolved population size also significantly increased, where the first experiment generated a population of 500 solutions (**Section 4.1**), the final experiment (**Section 5.3**) evolved a population comprised from 25,000 solutions. Both the size of the superblock and the size of the population was facilitated through the implementation of regulation within the design problem, as by doing so, the simulation run time and computational load of each experiment became more optimised. This was key in demonstrating the success of the tools and methods developed in generating populations of solutions that are optimised to different environmental conditions associated with different climatic contexts. More importantly, this highlighted the necessity and success of adapting the model to the climatic conditions of the urban tissue being examined and optimised for while maintaining the same principle approach to the formulation and mode of expression of the design problem. However, a limitation was that the evolved superblocks were generated as different entities; addressing this through their analysis on the scale of an urban tissue would allow for relationships to be generated between different superblocks that are driven by the relationships already developed between the blocks within each superblock.

4. *Can the data outputted by the evolutionary simulation be used as a feedback mechanism to reformulate the design problem in order to construct a more efficient simulation?*

The significance of the statistical analysis of the numeric data associated with each solution in the population was demonstrated through each of the experiments conducted. The role that this analysis played on the formulation and reformulation of each experiment was pivotal in the progression and advancement of each consequent experiment towards evolving a population of solutions that efficiently navigated the fitness landscape towards global optima, yet maintained within it sufficient variation that are optimised for each of the fitness objectives. The tools developed were pivotal in streamlining the analytic process in highlighting emergent patterns that are only visible through the analysis of the fitness values for each solution both independently as well as comparatively. Finally, the analysis of solutions within the population and their ranking through external selection criteria was key in facilitating the selection of a solution set from the population through its analysis of criteria that were independent to the simulation. However, although successful, the selection methods employed are contingent on the fitness values of each solution within the population; allowing for selection criteria that were completely independent from the fitness values would allow for the selection of a solution set that is directed by design decisions external to the ones defined in the design problem.

5. *Can the algorithmic application of a biological evolutionary process dynamically control variation within the population without external drivers?*

Through the experiments conducted in **Section 5.4**, the incorporation of a population-based fitness criterion as a fitness measure that was derived from the analysis of the variance value of each solution within the population, allowed for the variation within the population to be controlled dynamically throughout the simulation run. Through maximising or minimising this fitness measure, the simulation was able to increase or decrease the levels of variation within each generation yet continue to optimise the population towards global optima. Additionally, through this dynamic control and incorporation of the analytic tools within the algorithmic loop, instances within the simulation that favoured some objectives over others by attributing an unintended weighting between the objectives was counter measured. This highlighted an emergent behaviour to the implementation of the population-based fitness criterion that was not anticipated, which is that it can also be used to drive the simulation towards maintaining an equal weighting between the optimisation of the different fitness objectives driving the simulation.

6.3. Contribution

The research contributes to two principal fields, *morphological variation within urban tissues* as a primary contribution, and *evolutionary computation in design* as a secondary one. In the former, the exploration of variation of form and space through the developed computational methods was successful in driving the evolved solutions towards shared morphological characteristics yet simultaneously retaining within each generation sufficient phenotypic diversity allowing each solution to independently respond to and optimise for each environmental condition; while in the latter, innovations to the workflow of evolutionary simulations in design provide new functionality; such as the application of regulatory mechanisms in the formulation of the design problem; reduced simulation run times; generation of large population sets; comparative analysis of all solutions from the population and the selection of any solution from any generation. The contribution to each domain is highlighted further below.

6.3.1. Urban Design

The developed computational tools and methods were applied in multiple urban tissues that aimed to prove the applicability of the developed methods as well as address urban challenges faced by the selected urban landscapes. The contributions to the morphological variation of urban tissues are outlined below.

The Biological Argument for Urban Development

Similar to how species in nature evolve and adapt to stresses in their environmental context, the research argues that the components that comprise the urban fabric must also evolve and adapt in a similar fashion (**Section 1.1**). As in nature, to be better prepared for changes in the environment, the species (or the urban tissue) must be comprised from a diverse set of individuals

that collectively optimise towards the immediate environment yet are diverse enough (both in their phenotype and their genotype, as well as both collectively and individually) to adapt to environmental stresses (**Section 2.3.3**). The experiments demonstrate that it is possible to evolve a population set that is driven towards similar morphological characteristics yet has the capability to retain within each generation sufficient phenotypic diversity that is independently optimised for each environmental criterion (**Sections 4.3.4, 5.2.4 and 5.3.4**).

Morphological Variation within the Urban Fabric

The research highlighted the modernist's approach of attributing an 'average' urban block – one that is presented as the 'best' solution for the urban environment, and thus is consequently arrayed across the urban landscape – and highlighted its failure to address issues of climate, topography, environment and demographics that are unique to each city (**Section 2.2.4**). More importantly, the research highlighted the necessity of addressing the criteria stated above within the same urban tissue, in which different blocks are better suited to different environmental conditions (**Section 2.2.3**). Thus, emphasising the significance of generating sufficient variation between blocks within the urban fabric (**Section 2.2.2**). Through employing the developed computational methods as a generative tool in three distinct urban tissues (**Sections 4.3, 5.2 and 5.3**), the research demonstrates the applicability of the developed approach in generating urban variation for design problems that are comprised from multiple conflicting objectives.

The Superblock

Throughout the research, the conducted experiments utilised the *superblock* as the basic geometric unit to which each design problem was formulated. Through its analysis, the superblock's significance as a unit that was large enough to allow for regional relationships to develop between neighbouring blocks, yet small enough to allow for each block to evolve independently towards the different fitness criteria running the evolutionary simulation; identified it as an efficient geometric primitive for the conducted experiments (**Section 2.2.5**). Within each experiment, the superblock's morphological characteristics and internal attributes were modified according to each urban tissue; moreover, as the computational methods progressed, the superblock's size (i.e. the number blocks comprising each superblock) expanded in line with the developed 3d modelling methods incorporated within the formulation of the design problem (**Section 5.3.2**).

Planned and Evolved Cities

The research presented two distinct urban types, planned and evolved cities. The differences between the two were examined and both advantages and disadvantages of both city types were highlighted. Through this approach, the developed computational methods were applied for generating urban variation for both a planned city (**Section 5.2**) and an evolved city (**Section 5.3**). The design problem for each experiment was formulated uniquely to the local environmental and climatic conditions of each urban tissue. More importantly, the primitive phenotype for each experiment was comprised from the existing block within each city, to which primitive

transformations (and in some cases, minor morphological attributes) were applied to the existing phenotype, with the goal of generating diversity within the population set that is optimised for each city's environmental context (**Sections 5.2.2 and 5.3.2**).

6.3.2. Evolutionary Computation in Design

The contribution of the research to the application of evolutionary computation in design is conducted through multiple fronts:

Incorporating Regulation within the Design Problem

The literature review highlighted the significance of the field of evolutionary development in progressing the biological field of evolution (**Section 2.3.5**), and the consequent lack of incorporating Evo-Devo principles in evolutionary computation, specifically within design. Among many other contributions, Evo-Devo highlights the role of genetic regulation in generating phenotypic variation through a limited toolset, and the efficiency in which this is achieved (**Section 2.3.4**). It is this principle that the research integrated within the process of the application of evolutionary computation in design. Through clearly delineating between three key components of the design problem; Fitness objectives, Gene Sequences and Body Parts, the research incorporated the regulation between these three components as a primary driver in the formulation of the design problem. In doing so, a greater understanding was achieved on the role of the three components in generating variation, and how their regulation can either increase or decrease how much variation is achieved among the phenotypes in the population. More importantly, its application was conducted and analysed in both single objective (**Section 4.2.3**) and multi-objective (**Sections 4.2.4 and 4.3**) problems.

Emphasising the Population over the Solution

The research addressed issues associated with design problems comprised from multiple *conflicting* objectives, and the necessity for reframing the design output to focus on generating a solution-set rather than a single solution (**Section 3.2**). Through the experiments conducted in **Sections 4.2 and 4.3**, the research compared the output of the same design problem approached through two different methods; in the first (**Section 4.2.3**), the conflicting objectives were reformulated in the design problem into one, equally weighted objective; while in the second, the simulation was allowed to simultaneously optimise for the four objectives independently (**Section 4.2.4**). In the former, the simulation quickly converged towards a single solution that was neither 'fit' nor 'unfit' for any of the objectives, while in the latter, the simulation's output was a varied solution set that had within it phenotypes that varied in fitness according to the different objectives driving the simulation. More importantly, through generating a population rather than a single solution, emergent behaviour among the simulation's progression was observed, in which although the evolutionary solver favoured a specific form, it retained within each generation multiple contrasting morphologies, thus highlighting the significance of the role that regulation plays in maintaining diversity both within the phenotype as well as the genotype (**Section 2.3.3**).

Exploration, Exploitation and the Fitness Landscape

The research highlights the significance of the fitness landscape on the balance between exploration and exploitation, and its impact on the degree of variation within the population. More importantly, the research addresses the role of the design problem, and how its formulation is vital to the complexity of the fitness landscape (**Section 4.2.2**). Through utilising the developed analytic tools (**Section 3**), the statistical analysis of the fitness values for each solution and the comparative analysis between the fitness values for each fitness objective highlighted the complexity of the fitness landscape (**Sections 4.3.4, 5.2.4 and 5.3.4**). In doing so, it was made clear whether the design problem required reformulation in order to more efficiently control how the solver is navigating the landscape. Thus, directing the simulation towards evolving a population set that is sufficiently diverse yet simultaneously optimised towards a global optimum.

Statistical Analysis of the Numeric Data Outputted by the Evolutionary Simulation

The research highlights the significance of prioritising the statistical analysis of the results outputted by the evolutionary simulation over the visual/morphological analysis of the outputted solutions (**Sections 3.3 and 3.4**). This is made clear when comparing the application of evolutionary computation for both small and large population sizes (**Sections 4.2, 4.3, 5.2 and 5.3**). More importantly, the research proposes two primary sets of analytic tools that examine the numeric data outputted by the simulation. The first set evaluates the fitness values for each objective independently (**Sections 3.5.2, 3.5.3, 3.5.4 and 3.5.5**), while the second set of analytic tools evaluates the numerical data for all fitness objectives comparatively (**Sections 3.5.6, 3.5.7 and 3.5.8**). Both sets are used for the analysis of the results outputted by all of the conducted experiments (**Sections 4.2.3.2, 4.2.4.2, 4.3.4, 5.2.8, 5.2.5, 5.3.4, 5.4.3.2 and 5.4.4.2**). Finally, the research brings to light the challenging task of *selection* (either a single solution or group of solutions) when generating large and diverse populations. Through evaluating and ranking the solutions in the population using various methods, primarily through the *parallel coordinate plot*, the research proposes alternative selection tools that can be utilised for choosing a single solution or a group of solutions through the comparative analysis of each solution's fitness values with the entire population (**Section 3.5.8**).

Emphasising the Genotype over the Phenotype

The research demonstrated the efficiency in which evolutionary computation can be applied within design. Through emphasising the genotype over the phenotype (**Section 3.6**), the developed approach focused on outputting the genome of each solution rather than its geometric translation. In doing so, the phenotype of *any* solution could be extracted from the population; thus, allowing for the comparative analysis of all solutions within the population, and in turn, the ability to select and visualise the morphological characteristics of any solution in the simulation's timeline (**Section 3.7**). Moreover, this allowed for a *drastic* reduction in the computational load required for running an evolutionary simulation in design.

Dynamic Control of Variation within the Simulation

The research acknowledges the need for a dynamic control of the exploration and exploitation of the fitness landscape, in which diversity among the population is directed 'live' within the simulation run. Through identifying the variance value of each solution in a given generation, and attributing this value as a fitness objective, the research demonstrated that this *population-based fitness criterion* is a robust mechanism to direct the levels of variation with the simulation (**Section 5.4**). Through modifying the algorithmic workflow of the SPEA-2 algorithm to incorporate the population-based fitness criterion (**Section 5.4.1.1**); a single objective problem was able to optimise while simultaneously maintaining diversity within its population (**Section 5.4.3**), while a multi-objective problem was able to counteract the unintended favouring of one fitness objective over the other (**Section 5.4.4**).

6.4. Impact

The impact of the research lies within the application of evolutionary principles, primarily focused on regulatory mechanisms, as a design tool for addressing complex design problems comprised from multiple conflicting objectives. More importantly, the significance of the statistical data outputted by the evolutionary simulation and the impact it has in allowing for the statistical analysis of the entire population (instead of only the last, or a few selected, generations) is a significant step forward for the application of evolutionary computation in design. It moves away from a 'black box' approach that blindly trusts the algorithmic solver, to one that highlights the necessity of using the analysis of the outputted data as a generative tool for the reformulation of the design problem; one that is more efficient and robust in directing the simulation towards a better navigation and balance between exploration and exploitation of its fitness landscape.

Prioritising the formulation of the design problem over the algorithmic application of evolutionary principles is vital in allowing for the analysis of the entire population, and the consequent extraction of any solution's phenotype from any generation within the simulation. Through identifying efficient geometric methods that allow for the modelling of a computationally 'lighter' phenotype, the conducted experiments were able to run simulations that generated population sizes of over 25,000 solutions without the need to simplify the design problem or the fitness objectives. This was critical in ensuring the developed methods are applicable regardless of the size of the population or the run time of the simulation.

The shift from a user, preference-based approach that associates a single solution for a design problem to one that attributes greater weight to the population as a design output is key for the application of evolutionary principles as a generative model in design. It must be made clear that the delineation between a single solution and a group of solutions does not pertain to the final output. It is understood that many design problems will require a single design solution, this is addressed through the proposed selection methods (**Section 3.5.8**), in which users are equipped with the necessary knowledge to make an informed decision based on each solution's ranking

within the population, thus facilitating the selection of a solution set that can be consequently visually analysed towards selecting a final solution. However, this shift, from the single to the population, pertains to the *process* of solving a complex design problem. The objective is to minimise (or completely remove) the user's personal preference in the design process in order to achieve a solution set that has independently optimised for each criterion without the user's influence (which usually results in favouring some criteria over others). Through a population-based approach, the *selection* task is delayed until *after* the solutions have been generated, thus avoiding the necessity for the user to select a solution at the end of each iteration of the algorithmic process. Although the presented research applies the above within urban tissues, it is applicable across a range of different design problems that vary in scale and complexity.

6.5. Limitations and Future Work

Three key limitations are observed in the conducted research. Each limitation is detailed below along with proposed solutions that comprise the 'next steps' of the research.

6.5.1. Regulation within the Algorithm

The research presents the regulation between the fitness objectives, gene sequences and phenotype's body plan as an integral part in the formulation of the design problem for generating morphological variation through the use of a limited toolset. However, there is no requirement by the algorithm itself for a clear delineation between the different components that are being regulated. Although there have been attempts to algorithmically incorporate evolutionary developmental principles in computer science, this has yet to manifest within design. The primary advantage of evolutionary computation in design is that the developed tools allow for non-experts in the field to apply evolutionary principles without the need for advanced knowledge in algorithmic processes. Therefore, any incorporation of Evo-Devo principles in the design process must ensure that this 'ease of access' continues, avoiding the association of evolutionary processes in design with advanced coding knowledge. Future research conducted by the author is currently addressing this issue, where the inputs for the evolutionary algorithm require the user to distinguish between the phenotype's body parts and specify which gene sequences control which parts (as opposed to current algorithms that only require the phenotype and genes as inputs, without the requirement for any association between them or a division of the phenotype into body parts).

6.5.2. Integrating Statistical Analysis within the Algorithmic Loop

The developed analytic toolset that evaluates the numeric data outputted by all solutions within the population is currently applied external to the evolutionary simulation. Indeed, it is necessary for the simulation to evolve solutions for there to be data to be analysed, however, as it stands, the simulation must complete (or be prematurely stopped) before any analysis can be conducted. The purpose of this analysis is to serve as a generative tool that loops back into the experiment setup and more efficiently reformulates the design problem. Although the presented research

has demonstrated the benefits of this, the manual approach is time consuming and requires (at times) multiple iterations for the design problem to be properly reformulated. Future research conducted by the author addresses this problem through integrating the analytic processes within the evolutionary simulation, where the solver is simultaneously evaluating the numeric data and producing the associated graphical output 'live' throughout the simulation's runtime. Moreover, benchmarks are being established that automatically highlight emergent behaviour in the evolved population and pinpoints the location of when the emergent patterns become evident (through highlighting the generation number in the analysis graphs).

6.5.3. Dynamic Variation in Complex Problems

Although the presented research demonstrated the ability to dynamically control variation within the population 'live' throughout the simulation's runtime, the complexity of the problem to which this was applied to was contained to a relatively simplified phenotype and equally simplified design problem. This was mainly due to the limitations of the evolutionary engine into which the experiments were conducted (*octopus.e*); it became more difficult to apply the population-based fitness criterion and efficiently extract (and analyse) the outputted data as the problem became more complex. To address this, the incorporation of the analytic tools within the evolutionary solver (detailed in the section above) is within a new evolutionary engine that is currently being co-developed by the author, in which there is a more direct link between the evaluation of each solution to the evolutionary engine, allowing for a more streamlined connection between the population-based fitness criterion and its incorporation within the design problem. More importantly, by doing so, the future research is also acknowledging the importance of being able to regulate the impact of the population-based fitness criterion within the simulation, through 'switching it on and off' (either manually or in response to the specified bench marks) at different stages throughout the simulation's runtime.

6.5.4. Selection Criteria Based on Clustering Methods

The parallel coordinate plot presented in Section 3.5.8 demonstrated an approach that aimed to analyse the simulation's output and rank the population according to external selection criteria that would facilitate the selection of a solution (or group of solutions) from the final population that was based on statistical analysis of the solution set rather than a visual analysis. The objective is to narrow the population to a smaller group, which could then be further analysed. Although through the parallel coordinate plot all solutions in the population were comparatively analysed and ranked, the ranking was primarily driven by either mean fitnesses or relative differences. An alternative approach to this would be to cluster solutions in the population according to similarities they share (either phenotypic or genotypic) and highlight a representative solution for each cluster that can be further selected and visually analysed. Through this approach, the analysis of the solutions in the population would significantly facilitate the selection of the final solution set as it is conducted on both the local level (between solutions) and regional level (between clusters).

Beyond the scope of this thesis, a clustering method has been developed as an additional selection tool through using K-means clustering. In doing so, any generation extracted from the population can be clustered according to a pre-set number of clusters. By clustering solutions within a given generation, the Populationist vs the Typologist argument discussed in **Section 2.2.2** is revisited; as it is no longer necessary to define a generation through an 'average' solution for that generation; through clustering, the solutions within a given generation are categorised according to how 'close' they are to each other in terms of fitness, and thus allowing for more localised representations of each generation yet simultaneously maintain a fair representation of the variation of solutions throughout the generation; thus driving towards the typologist approach through a more localised populationist method.

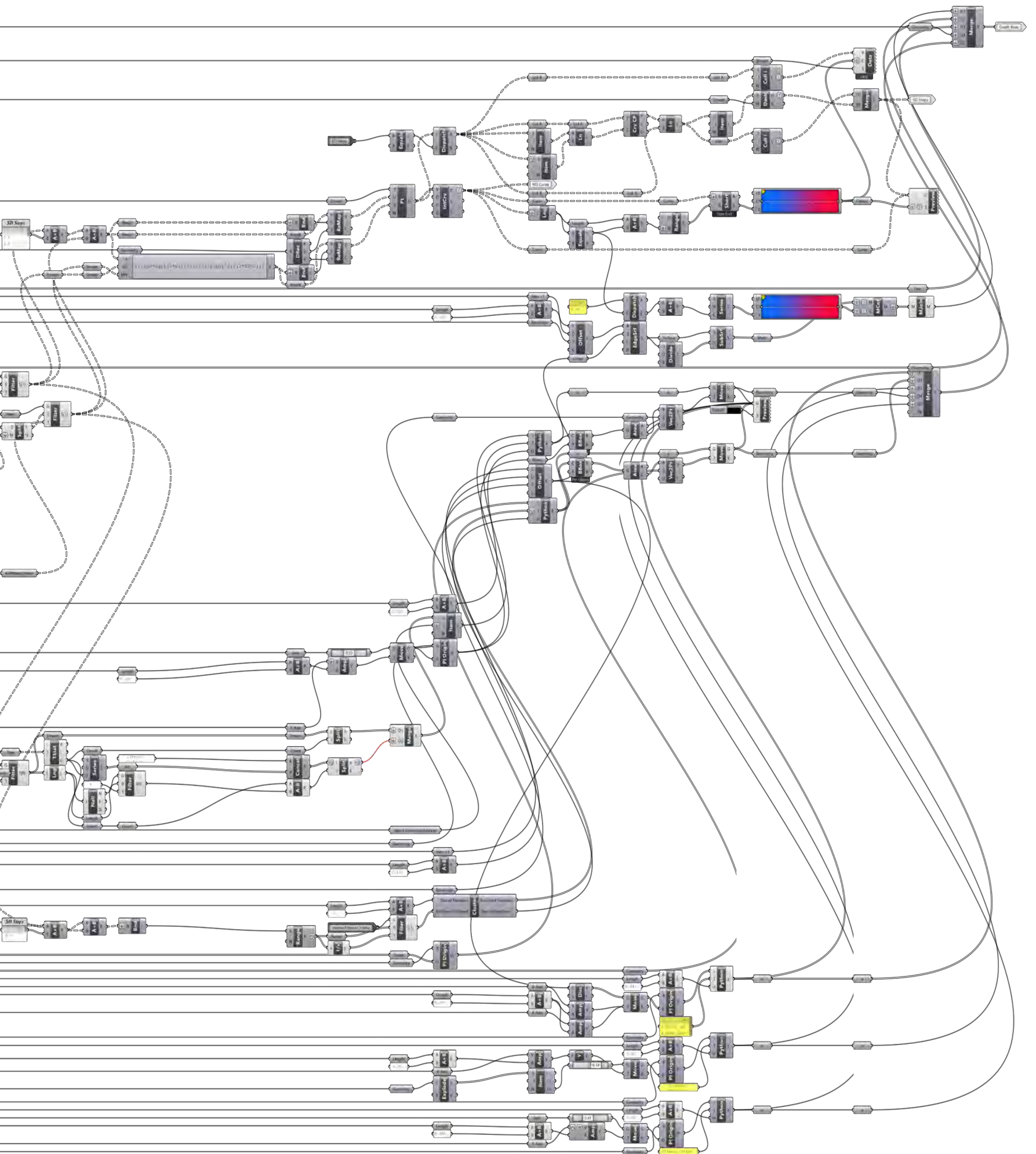
The potential to expand upon this in future research is the investigation of alternative clustering methods that would facilitate a greater degree of control and information of the solutions being clustered, primarily, through '*hierarchical clustering*', in which not only are solutions clustered according to how similar their fitness values are to one another, but also maintaining a hierarchical 'path' that maps each solution's history within the population; i.e. from which parents the cluster of solutions have descended from. This would allow for greater insight on the evolutionary patterns emergent to the evolutionary simulation, and would allow for the potential of 'tracking' specific morphological traits and discovering their origins (or cause thereof) in the simulation's experiment setup.

Appendix I - GHA Components

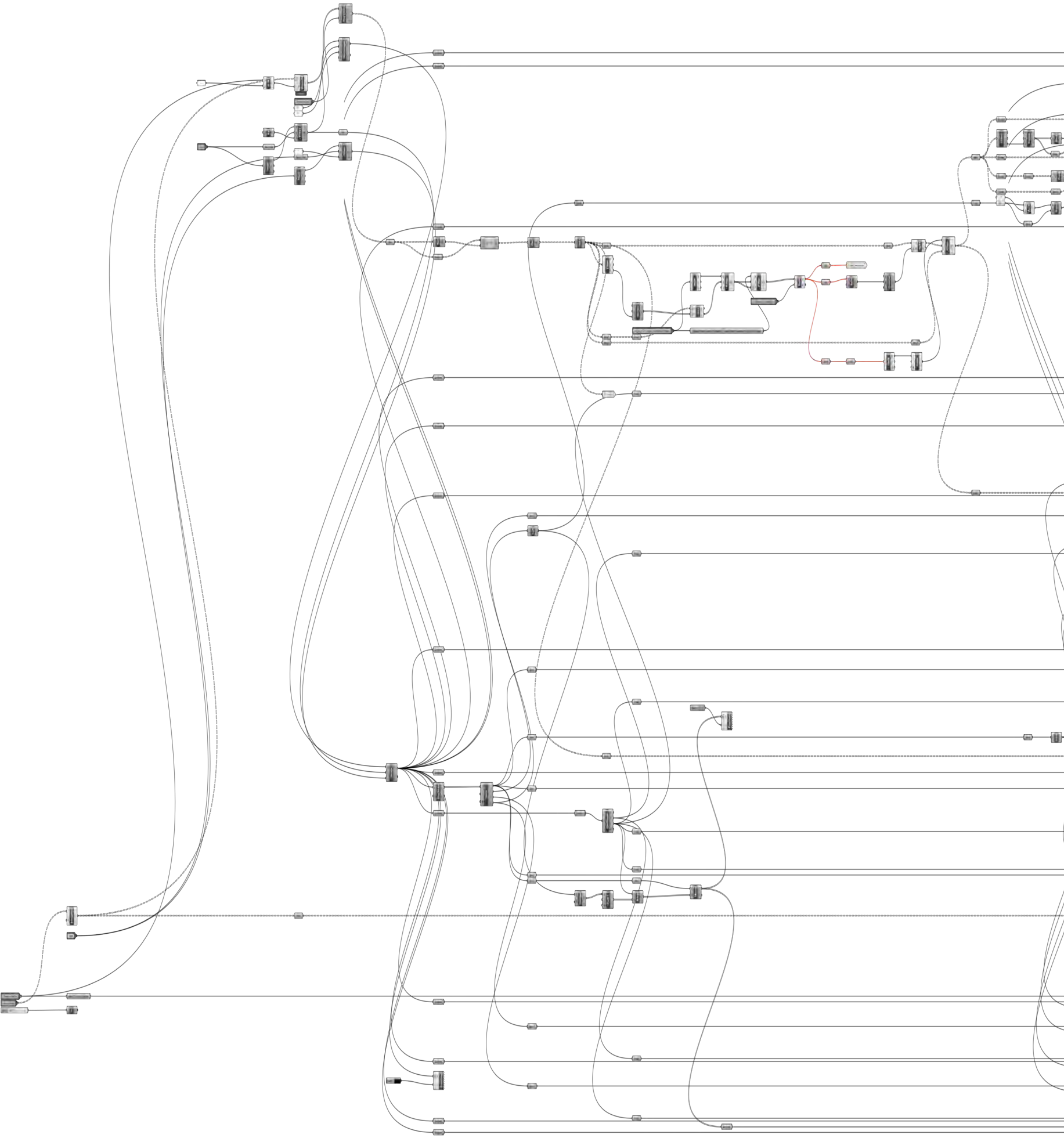
The GHA files for the tools developed and presented in **Chapter 3** are presented in the following pages. The GHA components can be downloaded in the electronic format of this thesis by clicking on the hyperlink below (note: To access the components in the downloaded link below, the software *Rhino 5 and Grasshopper 3D* is required:

[DOWNLOAD GHA](#)

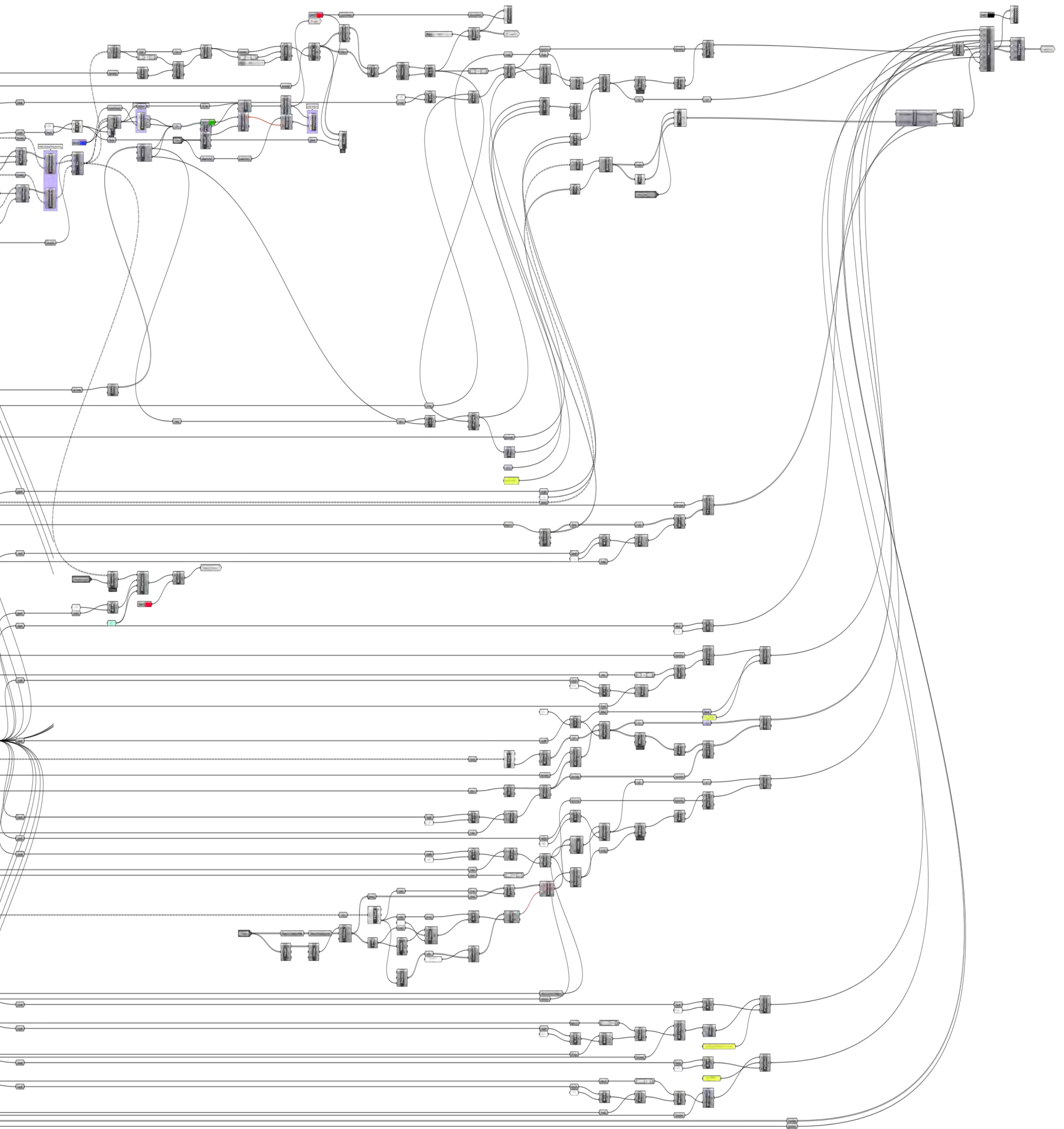
Standard Deviation Chart GHA File



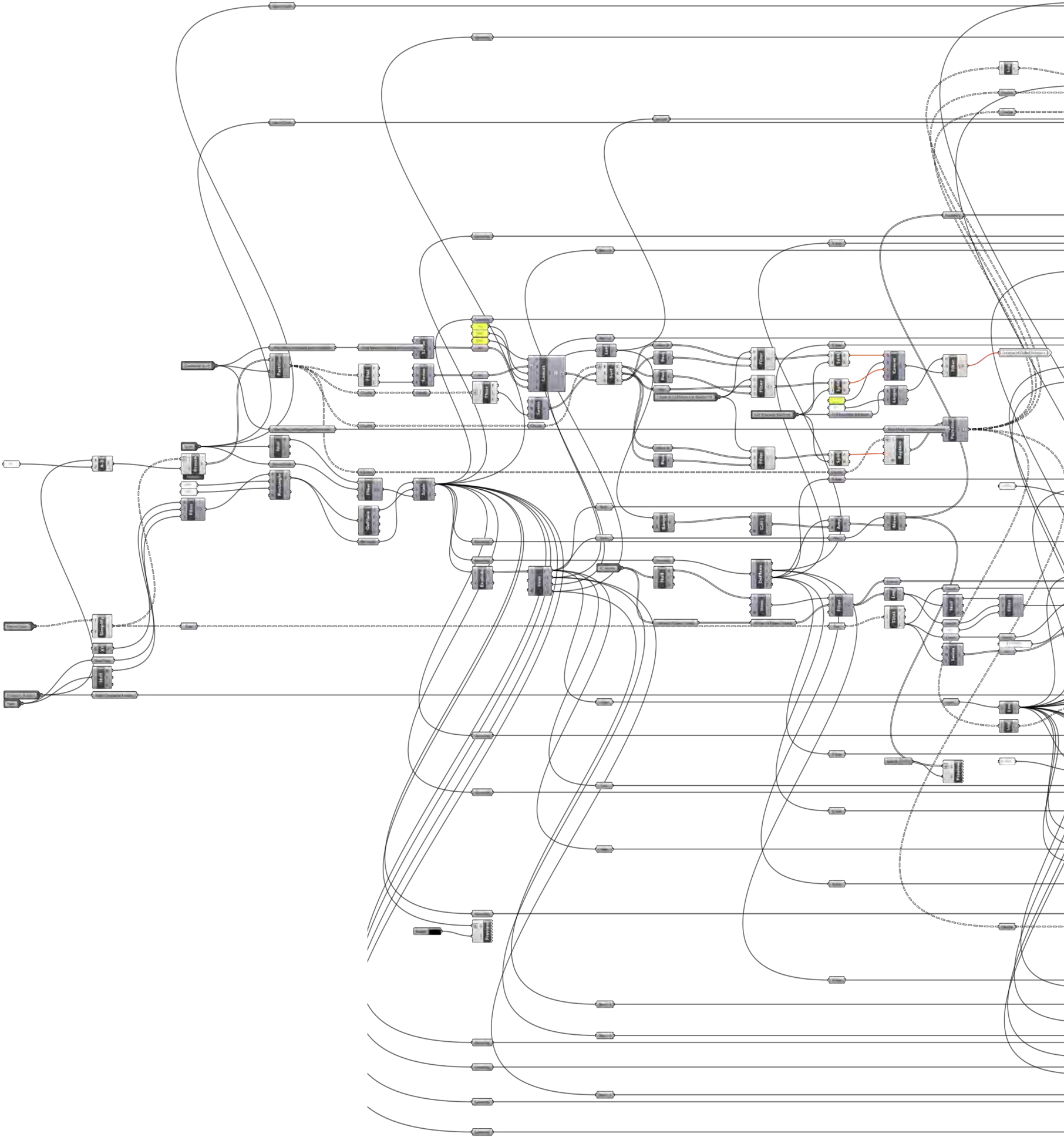
Standard Deviation Trendline Chart GHA File



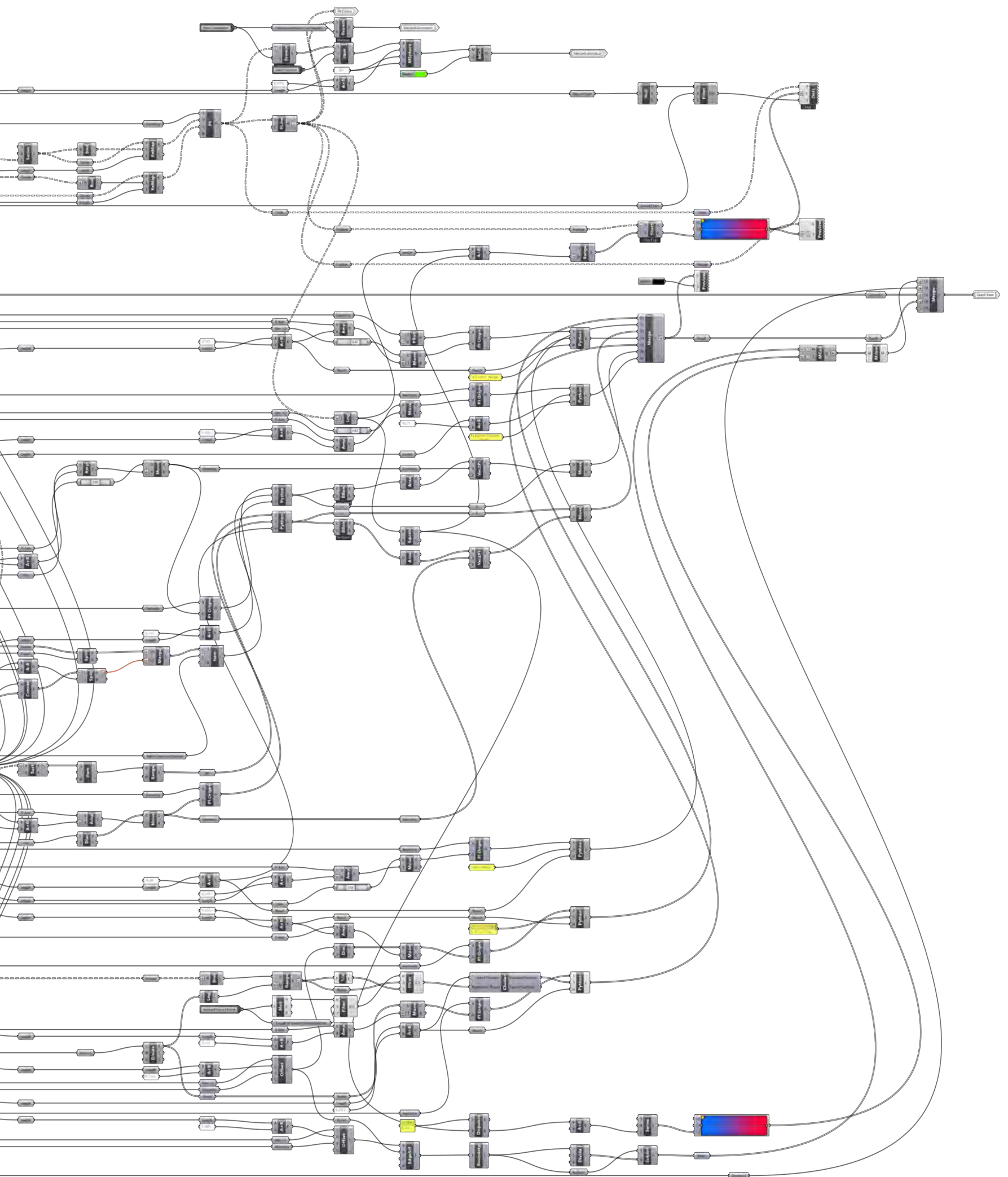
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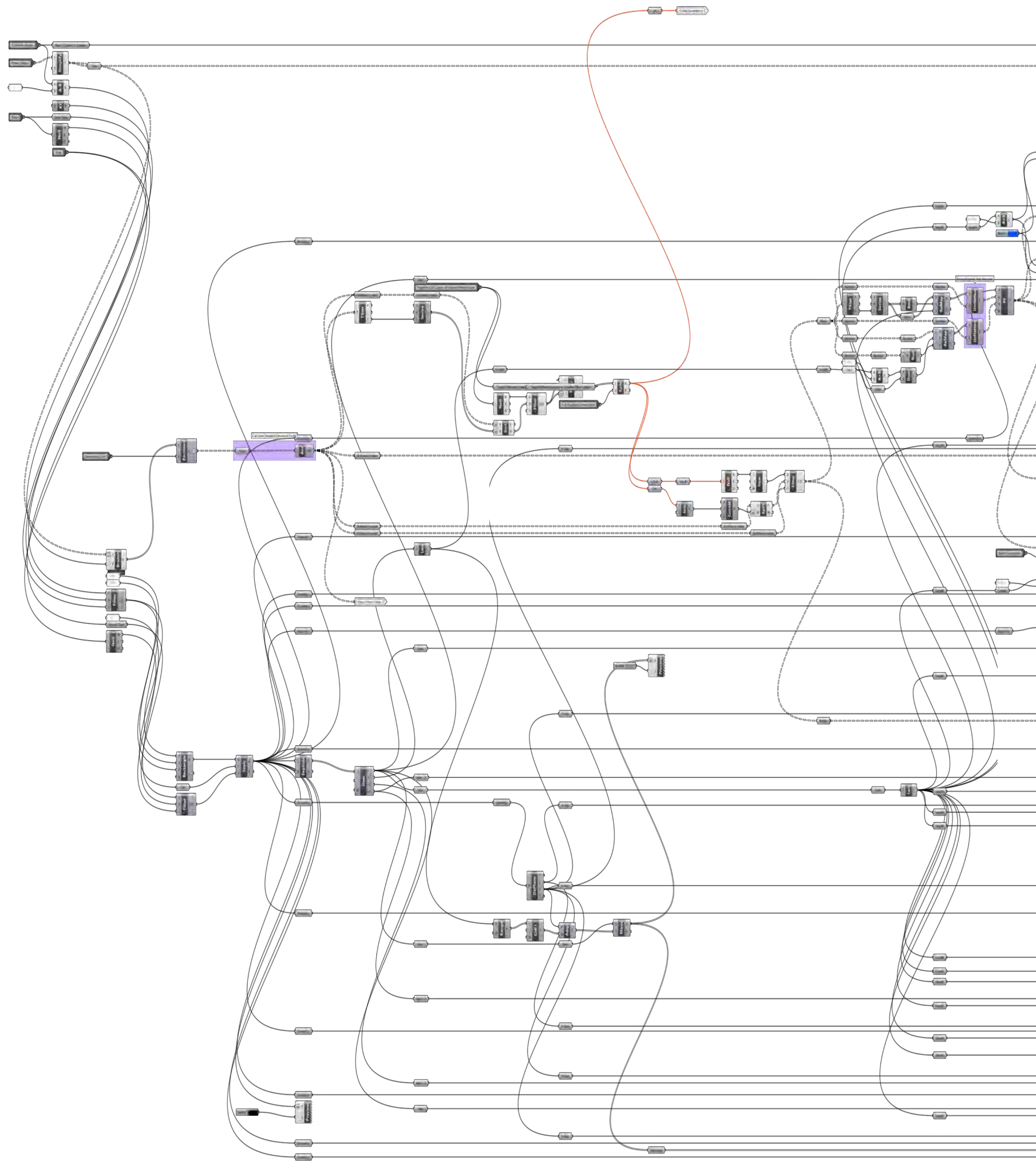
Fitness Values Chart GHA File



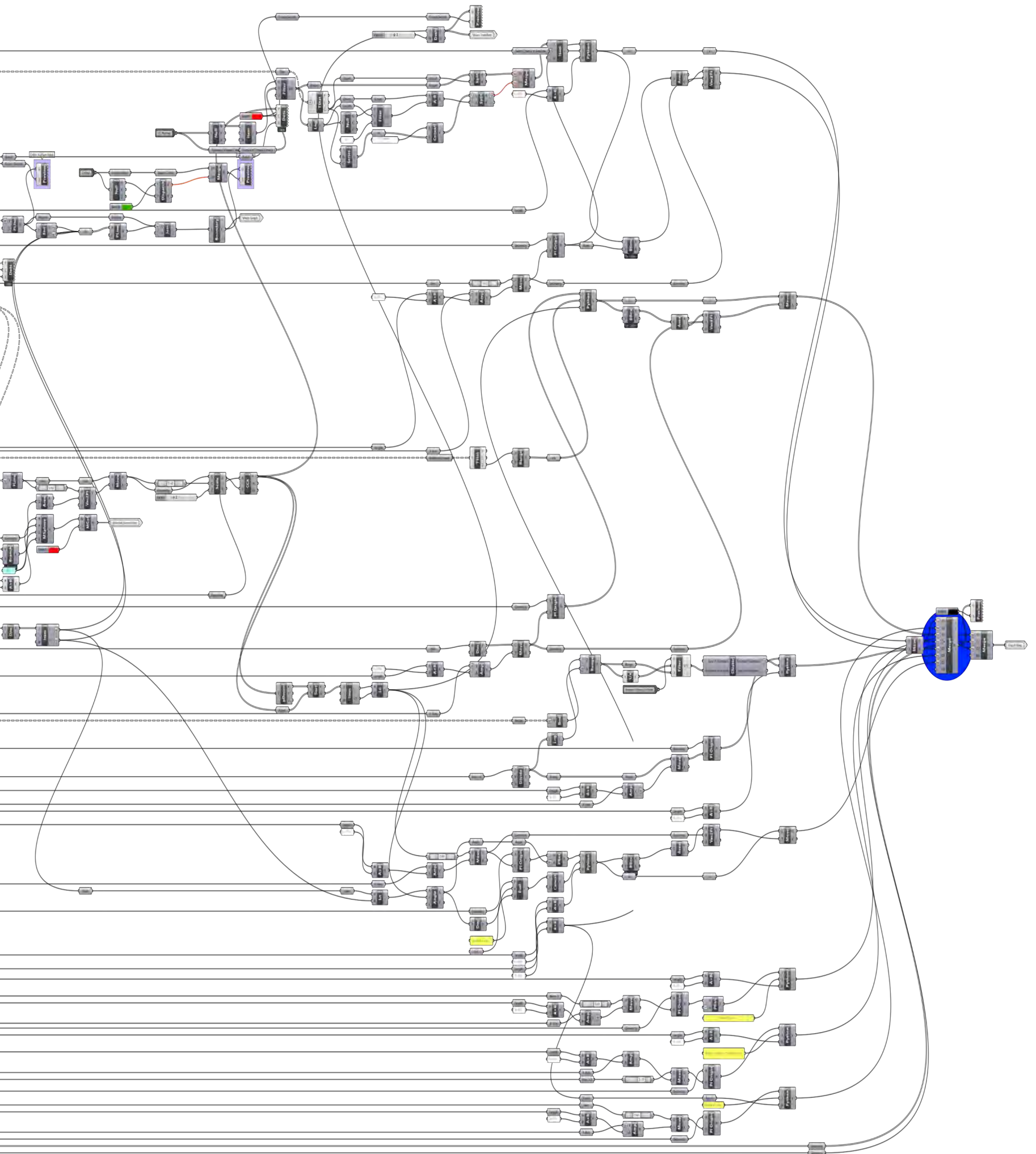
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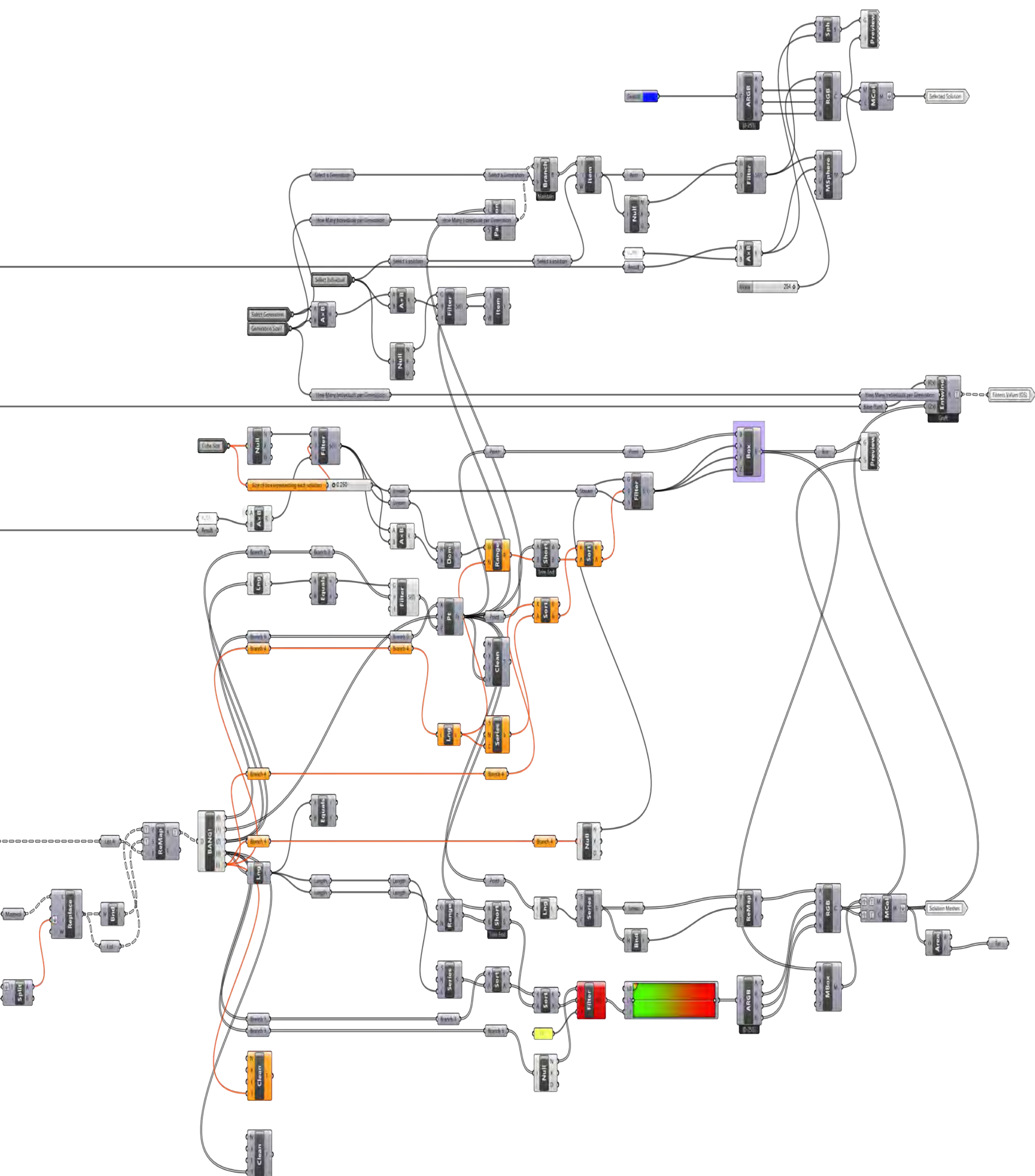
Fitness Values Trendline Chart GHA File



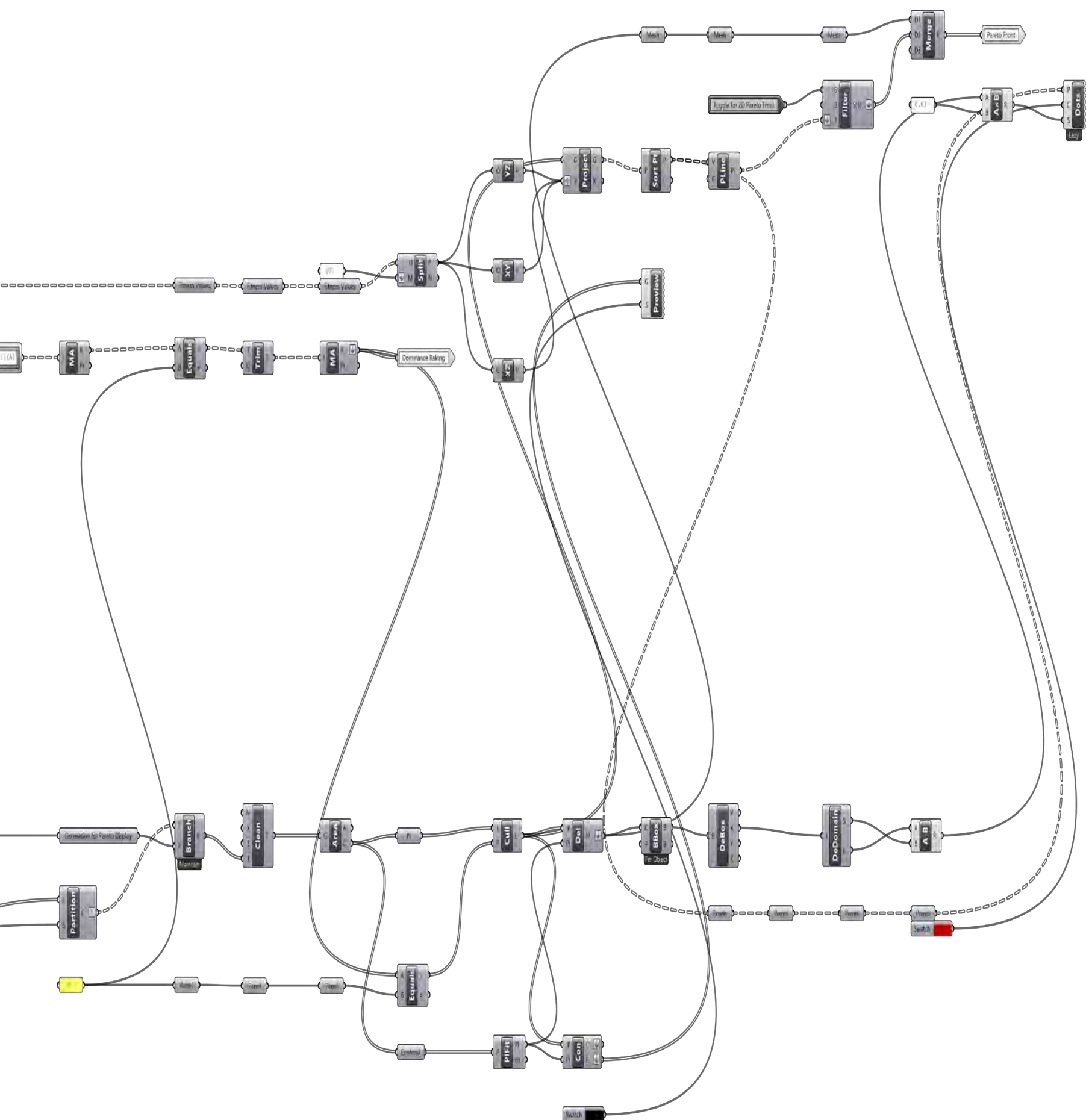
Fitness Values Trendline Chart GHA File



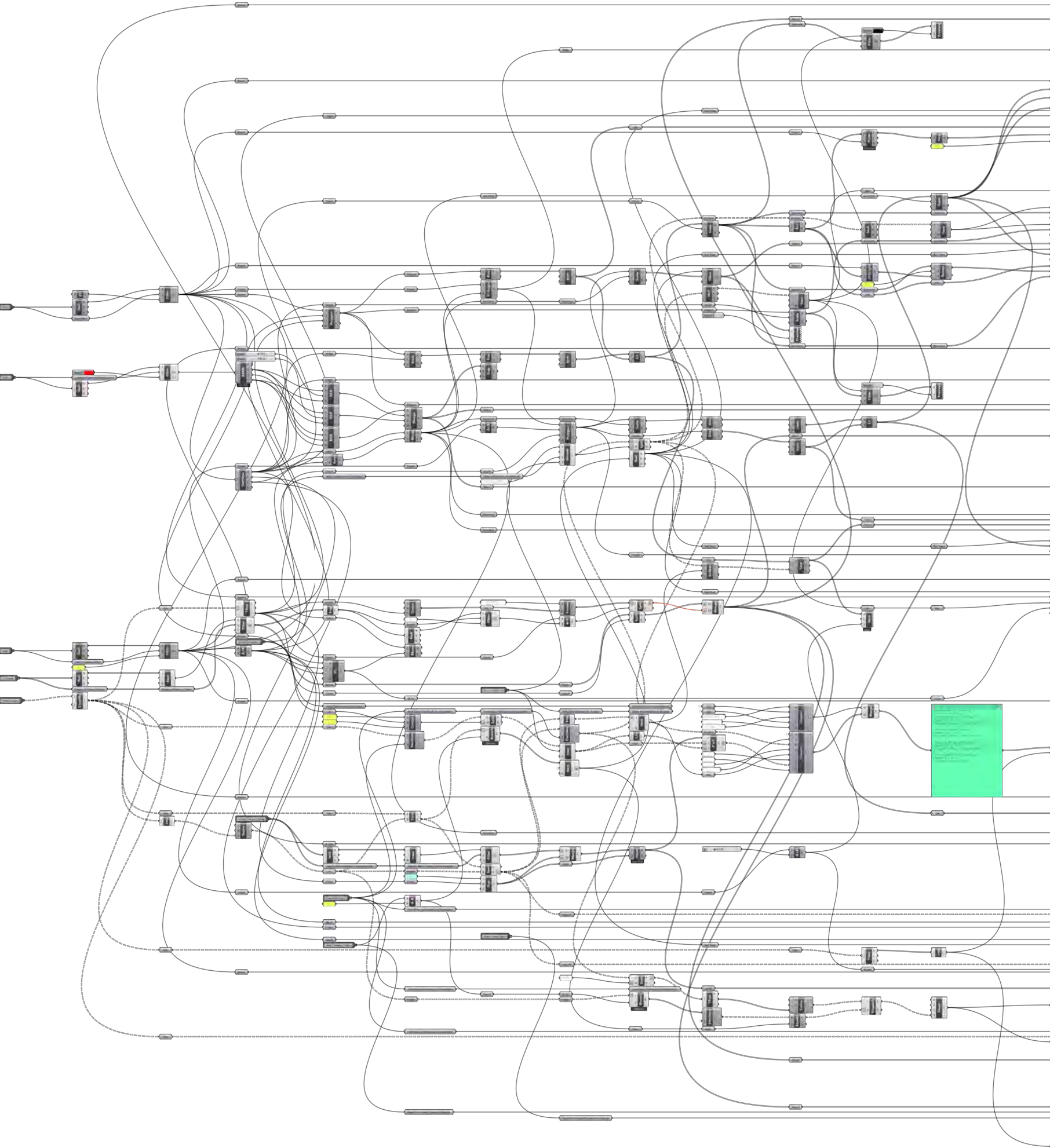
Objective Space Chart GHA File



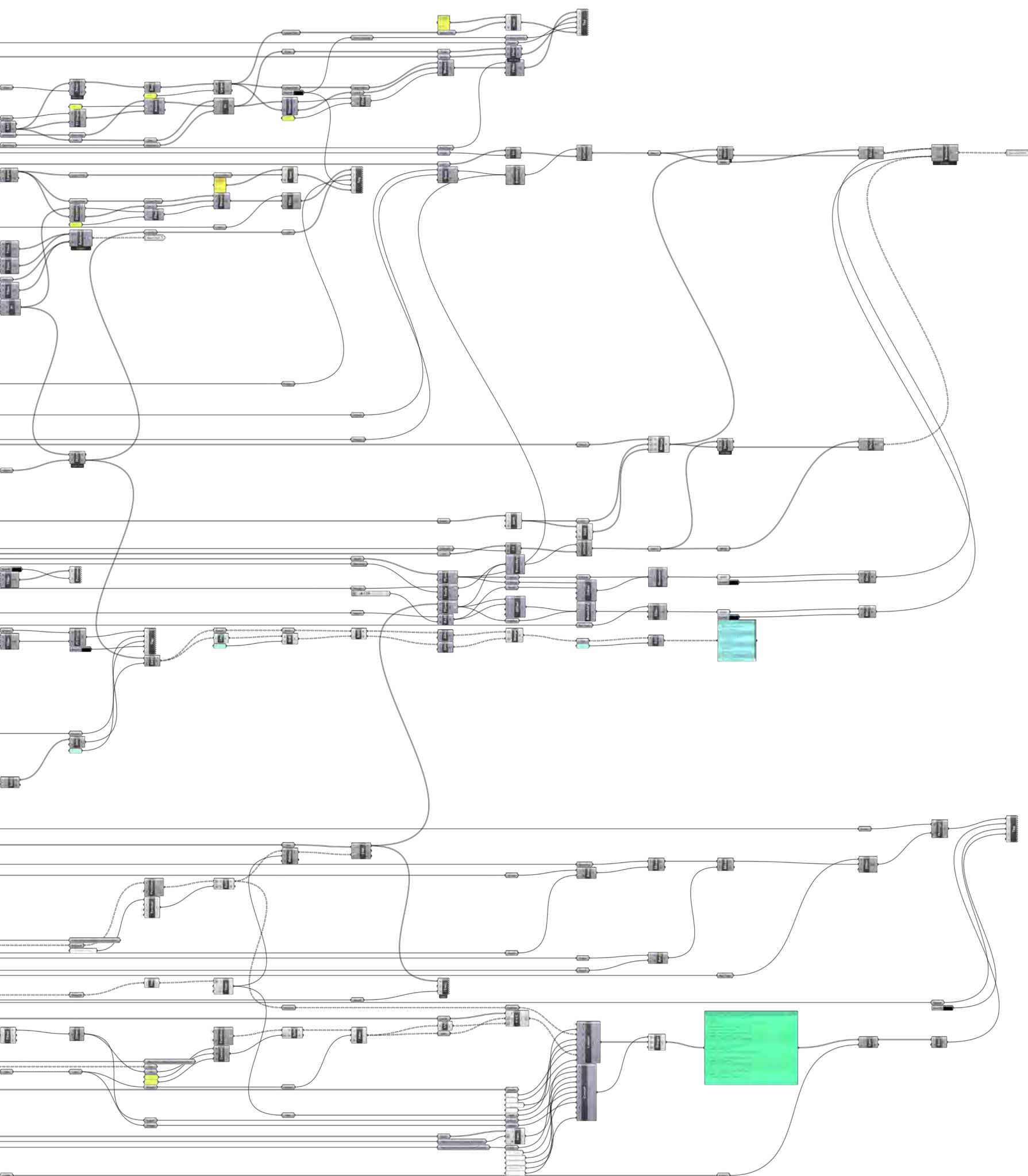
Pareto Front GHA File



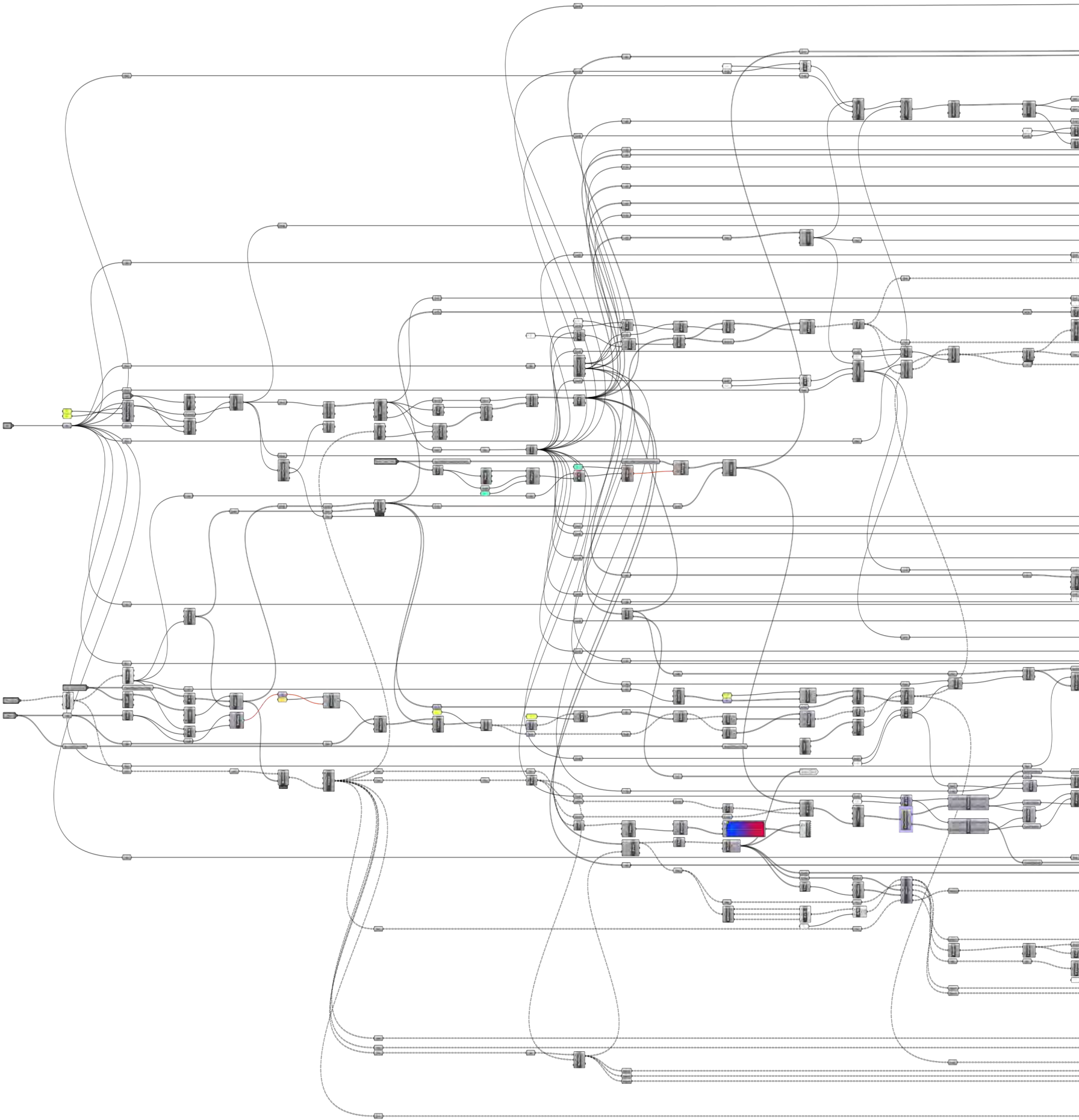
Diamond Fitness Chart GHA File



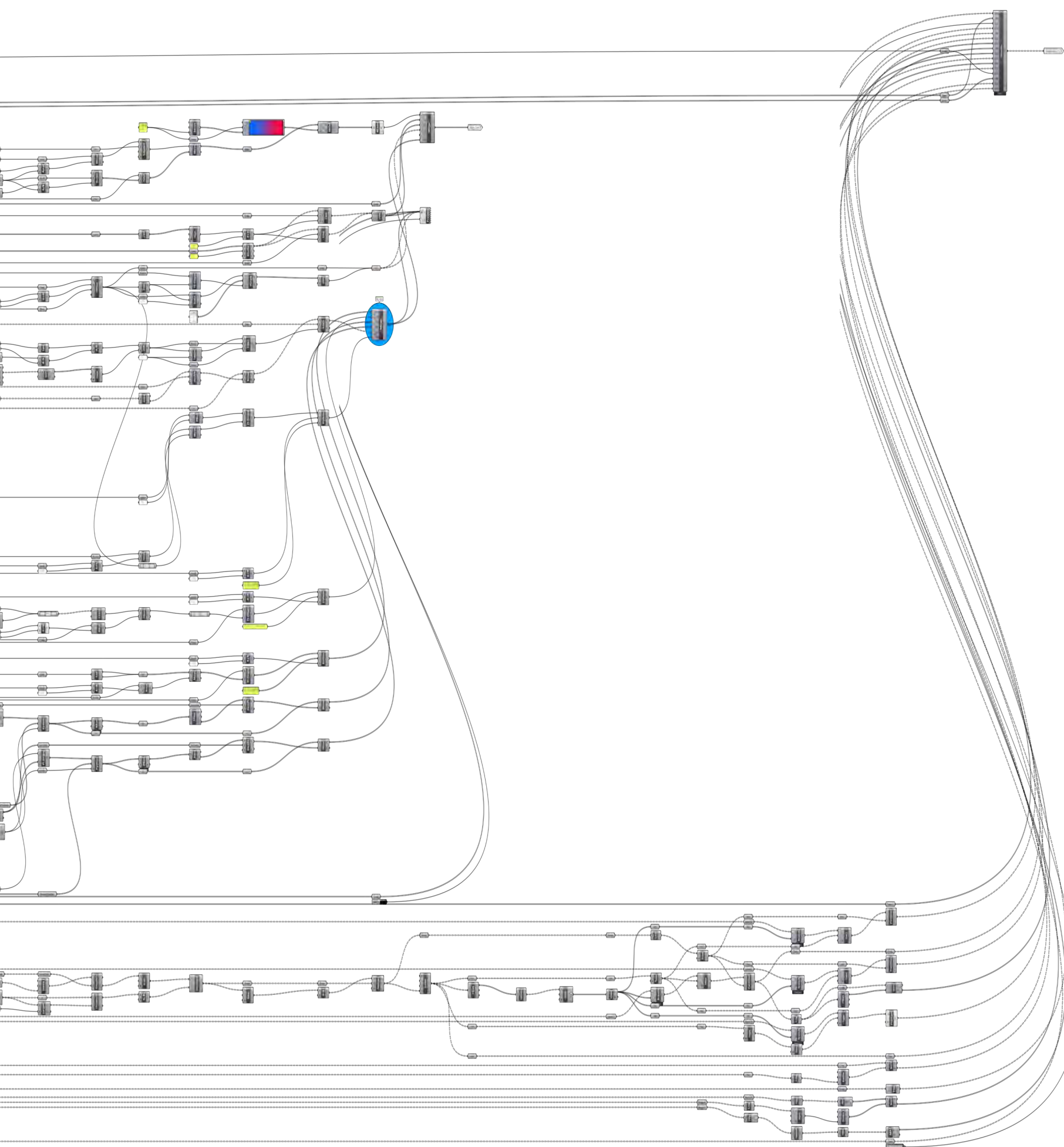
Diamond Fitness Chart GHA File



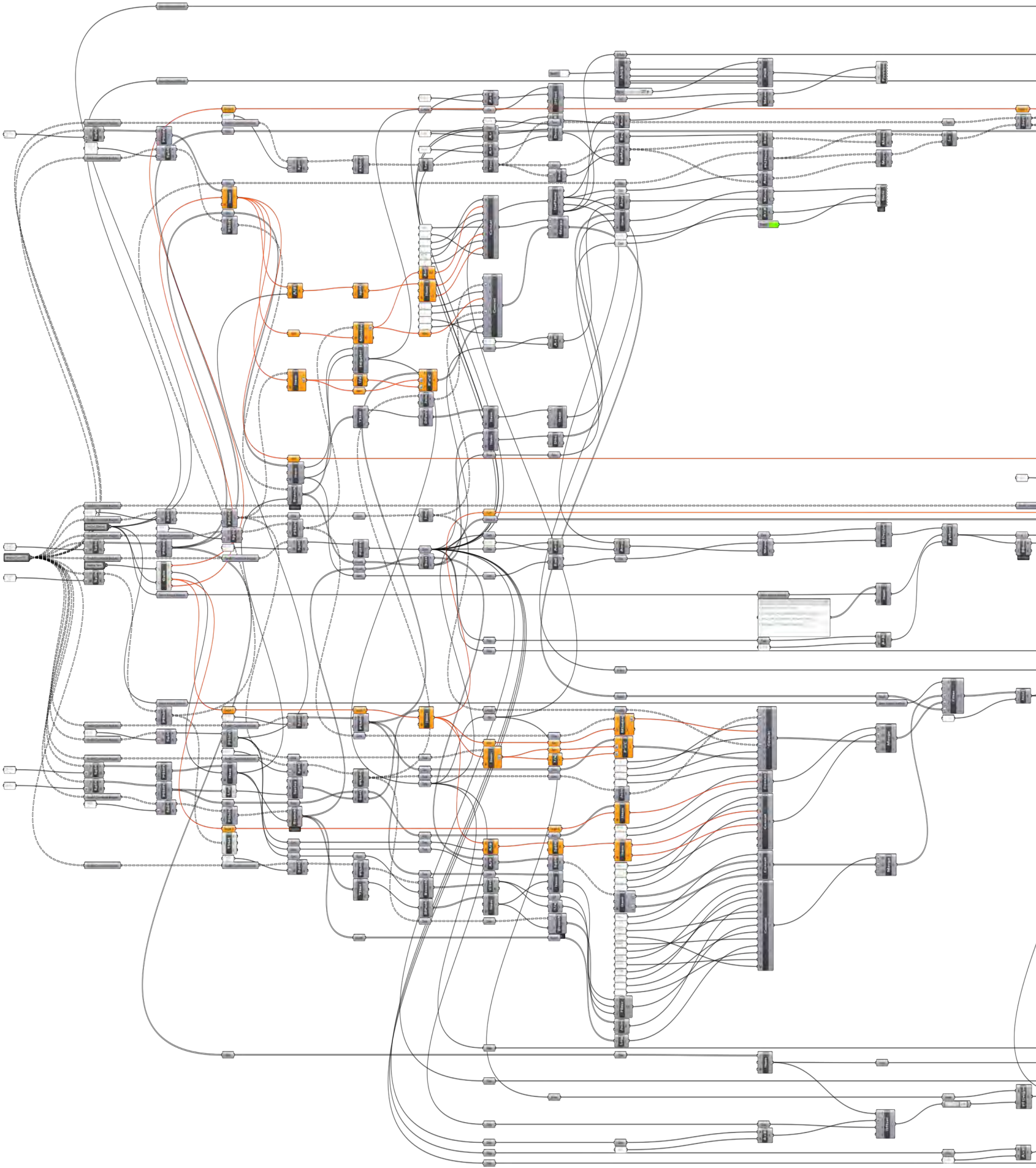
Parallel Coordinate Plot GHA File



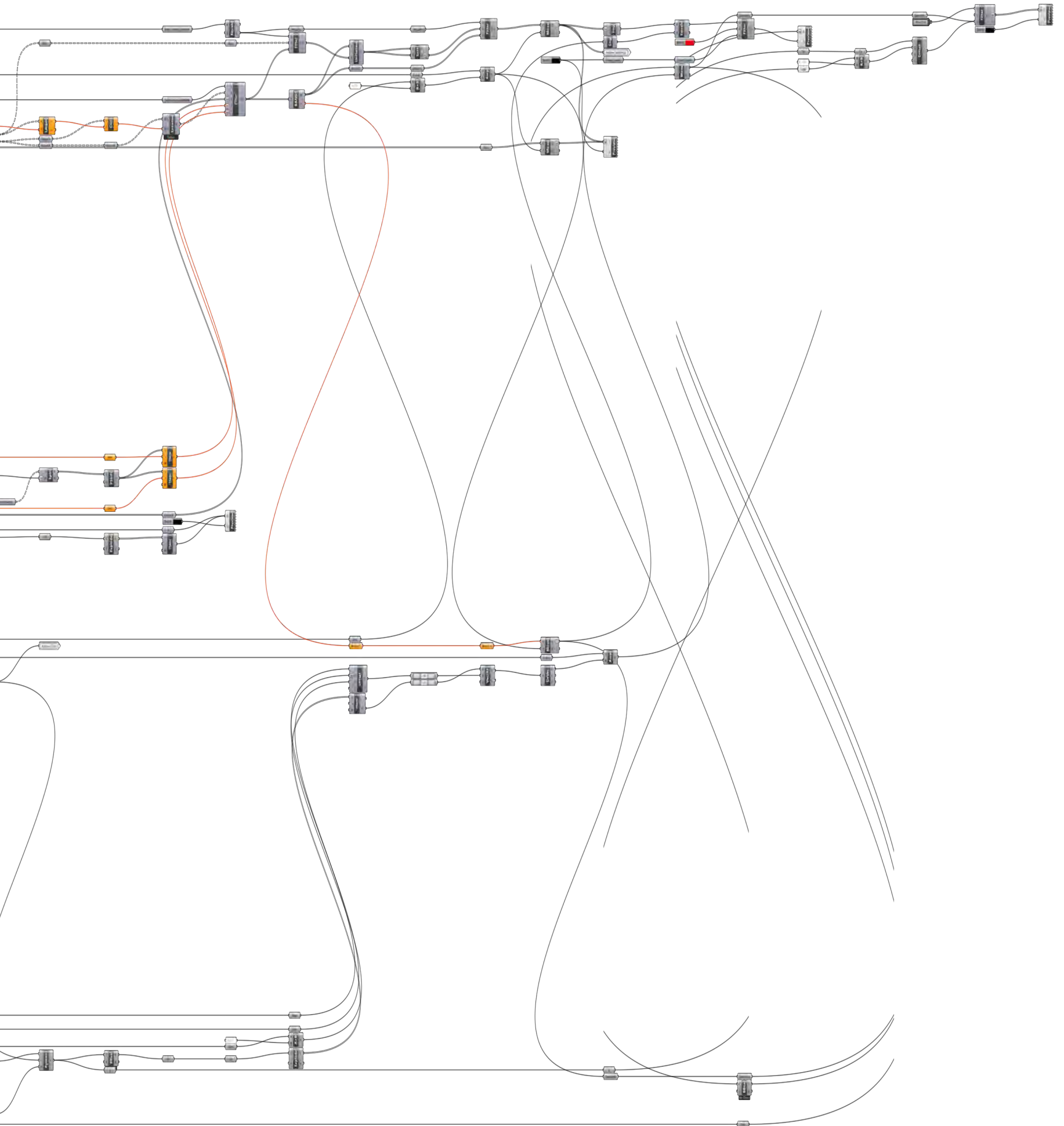
Parallel Coordinate Plot GHA File



Parallel Coordinate Plot Analysis GHA File



Parallel Coordinate Plot Analysis GHA File



Appendix II - User Testing

The methods developed within this research have been packaged and incorporated in the software ‘Wallacei’, which was developed with co-researchers in the field, Milad Showkatbakhsh and Yutao Song.

In the research presented in this thesis, the developed tools are independent from the evolutionary algorithm, i.e. the evolutionary algorithm must first be applied to the design problem, after which the results are extracted from the algorithm and used as input parameters for the developed tools. Therefore, the process is a 2-step process. In Wallacei, this 2-step process is packaged into one, where by starting the evolutionary algorithm, the developed analytic tools presented in chapter 3 are automatically applied to the simulation’s results upon the algorithm’s completion. This approach has made the application of the methodological workflow presented in the thesis more streamlined.

Through this, Wallacei has been used in multiple workshops between the months of February and June of 2019, allowing users from different backgrounds to apply the developed methods in their work, in which they tested the different analytic methods developed and examine their utility in applying evolutionary processes in design with a greater emphasis on understanding the results of the evolutionary simulation and its impact on reformulating the design problem.

The following table lists the workshops and presentations held in the period between February and June of 2019, followed by feedback provided by users of Wallacei. The chapter ends with samples of work created by users of the tool.

Workshops

#	Date	Program/Institution	Location	Length
2	January 2019	Bartlet, UCL	UK	1 week
3	March 2019	Architectural Association Visiting School, AA	Japan	2 weeks
4	March 2019	Chinese University of Hong Kong	Hong Kong	2 days
5	April 2019	ShenZhen University	China	2 days
6	April 2019	Queensland University of Technology	Australia	1 day
7	April 2019	University of Newcastle	Australia	2 days

Presentations

#	Date	Program/Institution	Location
1	March 2019	Osaka University	Japan
2	March 2019	Buro Happold	Hong Kong
3	March 2019	Pratt Institute	USA
4	April 2019	Shenzhen University	China
5	April 2019	Brisbane Computational Design Group	Australia
6	April 2019	Nettleton Tribe	Australia
7	April 2019	Architectus	Australia
8	April 2019	BVN	Australia
9	May 2019	Bristol University	UK
10	May 2019	Brydon Woods	UK
11	May 2019	UHA	UK
12	May 2019	Heatherwick	UK
13	Jun 2019	Wilkinson Eyre	UK
14	June 2019	Grimshaw	UK
15	June 2019	Prior and Partners	UK
16	June 2019	Bauhaus-University Weimar	Germany
17	June 2019	Pan Arab Consultants (PACE)	Kuwait

Feedback

Muge Belek Fialho Teixeira - Lecturer in Interior Architecture at the Queensland University of Technology

"Wallacei is an innovative and creative tool for the use of Evolutionary Algorithms in Architectural Designs. Through full integration into the design environment, Wallacei provides fast and thorough renders, allowing the user to visualise all the possible generations as well as contextualise the data with legible charts and diagrams".

Lorenzo Franceschini - BIM & Parametric Architect at Enzyme APD, Hong Kong | AAVS Osaka Programme Head

"Wallacei brings the digital optimisation to a new level, especially for what concerns the visuals. Giving the possibility of evaluating the results not only by their morphology but also thanks to the great charts and graphs makes discussion over the topic much easier".

Jorge Benítez Gardeazabal - Managing Director & Co-Founder of Enzyme APD | Graphisoft Registered Consultant.

"Optimising is a big part of any architect job. Whether this optimisation is manual, based on experience or automated, it's always a challenge to understand the implications to the different aspects of the projects and how the optimisation of those particular variables affects other performance parameters. Wallacei helps us to understand the data, the implications and possibilities that we'd never think of. And all this with a simple and beautiful interface that our clients love! To us it been a game changer, helping getting new business opportunities and helping us in our decision making process".

Irene Perez Lopez - Senior Lecturer and researcher, School of Architecture and Built Environment, University of Newcastle, Australia.

"I would apply Wallacei in Design Studio, research and design-led projects to test urban environment and architectural design problems. By building the model and formulating the correct question/s, Wallacei could be transformed into a very powerful tool to check viability and variability of projects and designs, ensuring a successful design. Wallacei is a very sophisticated tool, which I still have to explore in deep. I assume the deeper the knowledge, the wider the opportunities. The Wallacei Workshop ran at the Schools Architecture UoN has been a spectacular learning-teaching experience".

Emidio Piermarini - Associate, Asia Computational Projects Lead, BuroHappold Engineering | Structures | Hong Kong

"I think Wallacei shows us a key change that is here to stay going forward in the AEC industry – using data and visualization of that data to drive decisions on the big problems we are facing as a species. The future of design is designers who can code and take advantage of powerful tools like these".

Antoine Saurat - Urban & Regional Planner at RECS International, Japan

"I have barely seen the tip of the iceberg when it comes to the enormous potential of Wallacei and evolutionary simulation to generate and analyze tons of solutions. In the field of urban design and planning, Wallacei can help to identify urban patterns and density optimums based on complex factors and objectives, including climatic, geographical and cultural features, which would be a historic first in the design of cities".

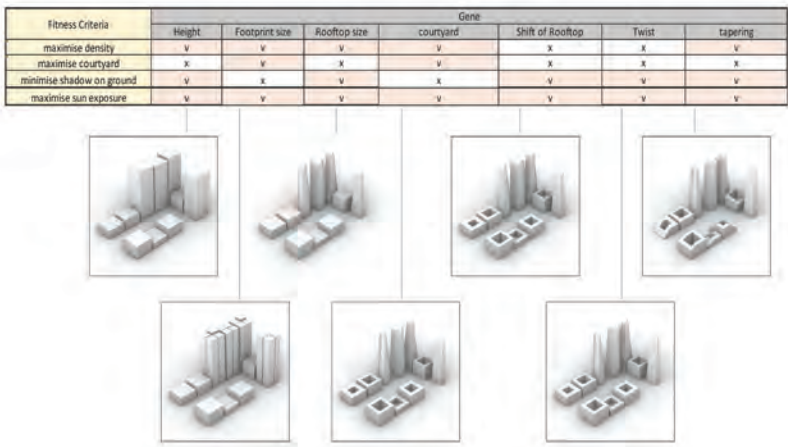
Adam Fingrut - Assistant Professor and researcher in architecture at the Chinese University of Hong Kong

"Wallacei is a fantastic tool for practice, teaching and learning about evolutionary algorithms in design. By placing emphasis on analysis – it helps us understand how to more effectively develop our code and refine our results through an iterative development cycle".

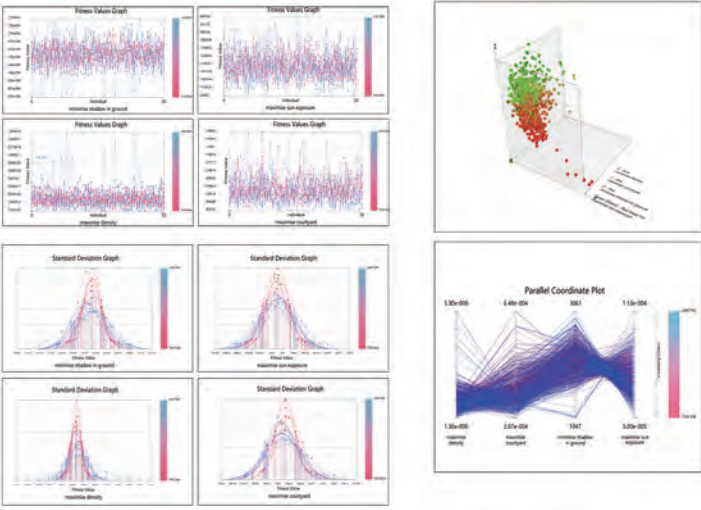
Workshop Results

The following pages showcase a sample of the results from the different workshops conducted at different universities and institutions. The various workshops asked students to apply the workflow and methods put forward in this thesis and develop their designs and design problems through a thorough assessment of the regulation between genes, body plan and fitness objectives, as well as a detailed analysis of the evolutionary simulation's results. The aim of the workshops was to apply the developed methods for a better and more efficient application of evolutionary methods for the design of urban clusters (except in the case of the AAVS in Osaka, where the developed methods were used in the design and construction of a scaled Japanese Pagoda). In all the workshops conducted, users had no prior knowledge or experience in utilising or applying evolutionary computation in design.

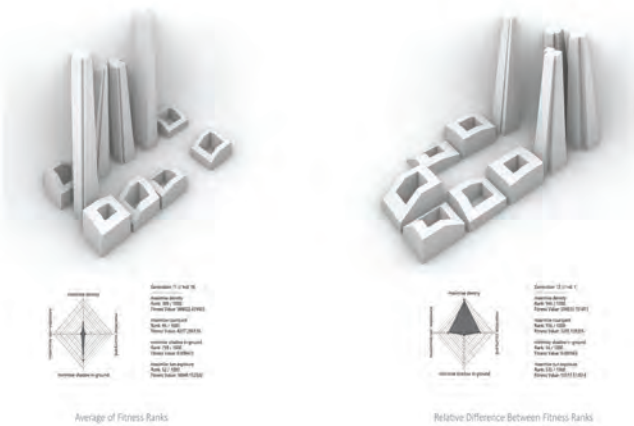
Formulating the Design Problem



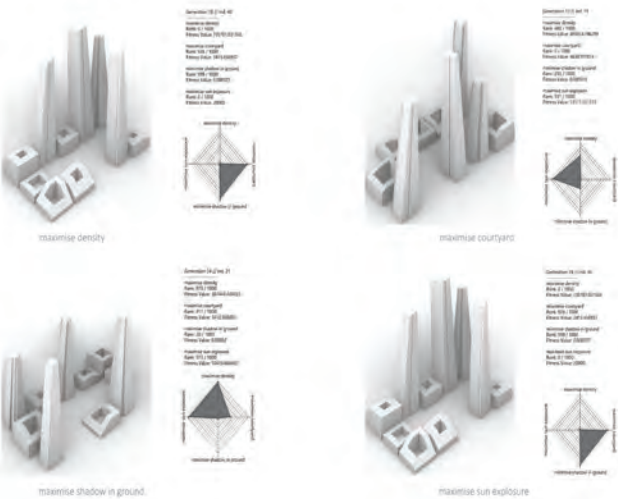
Analysis Graph



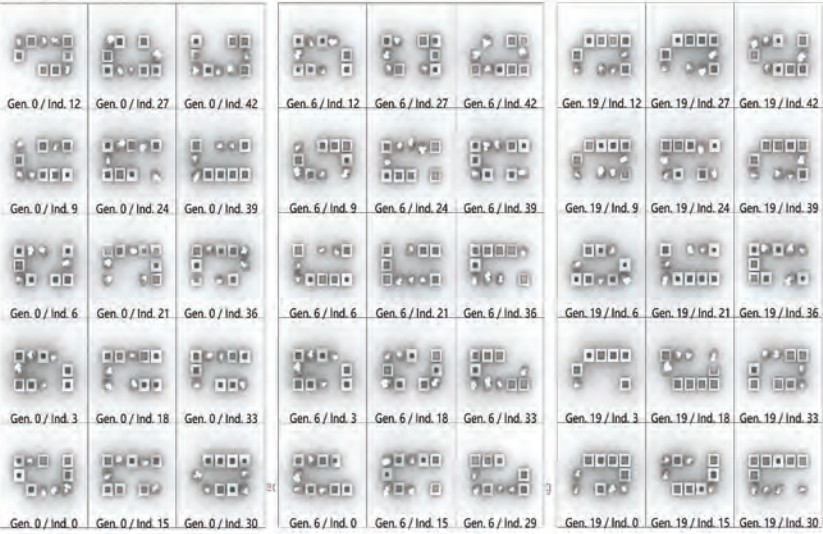
the most justified solutions



Best population for each objective

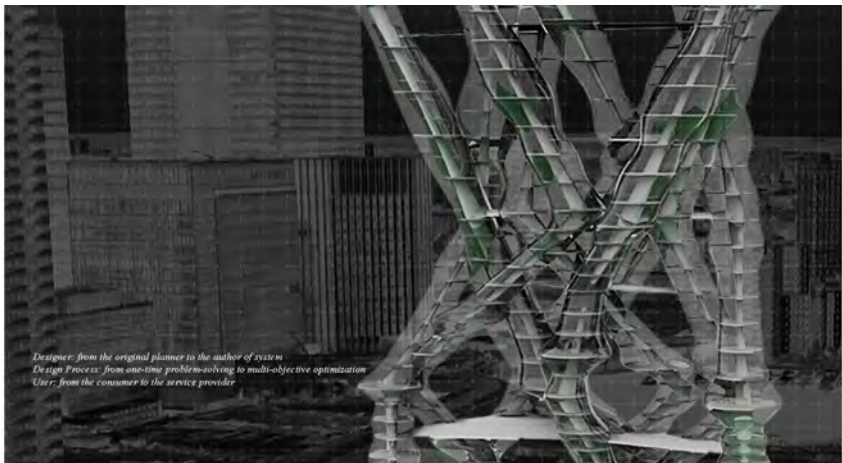
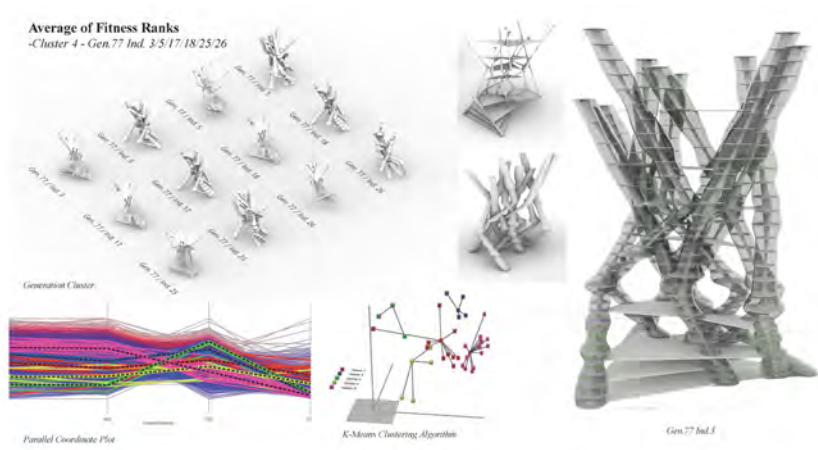
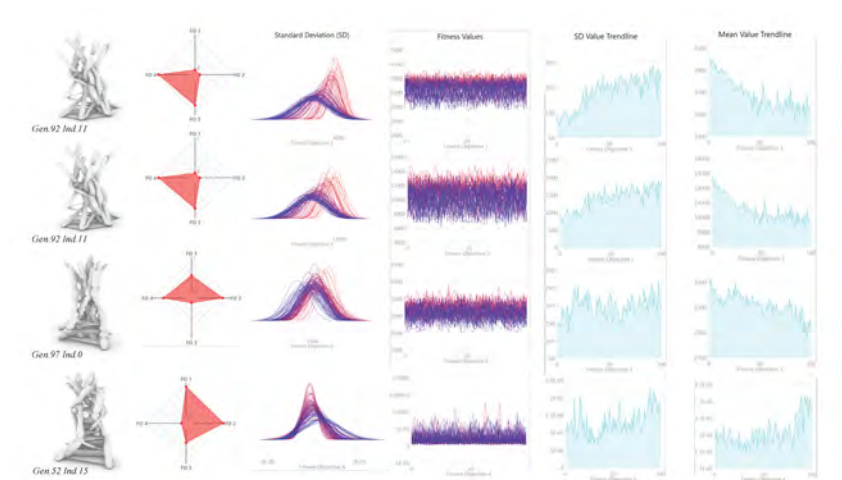
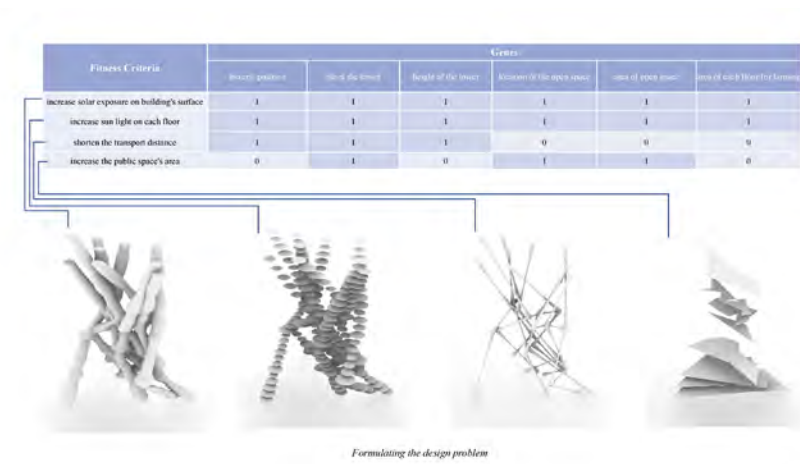


Population

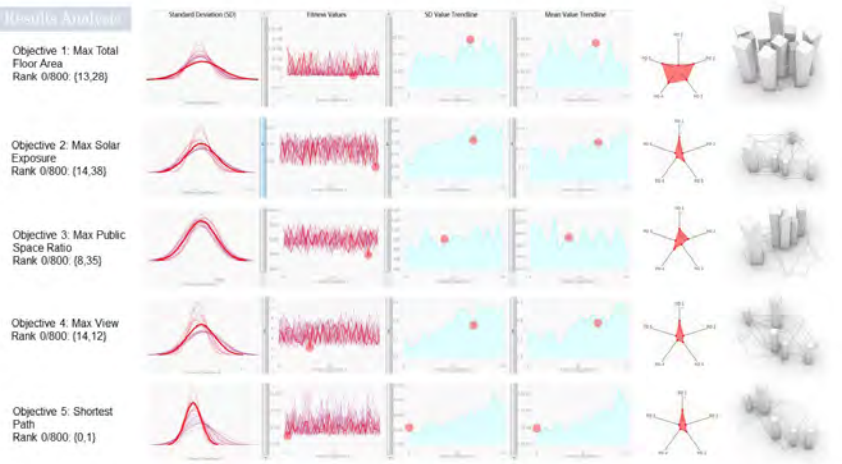
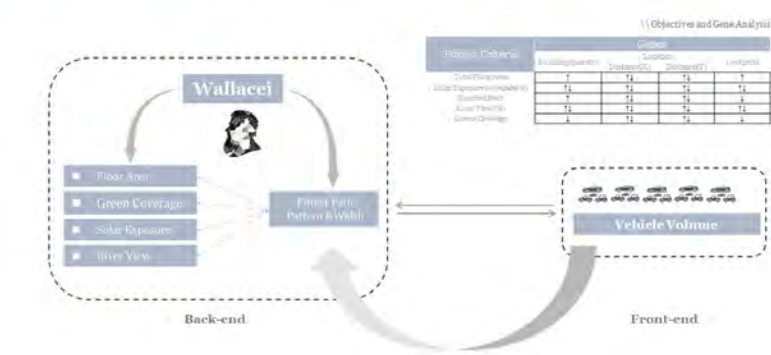


Urban Variation Through Evolutionary Development

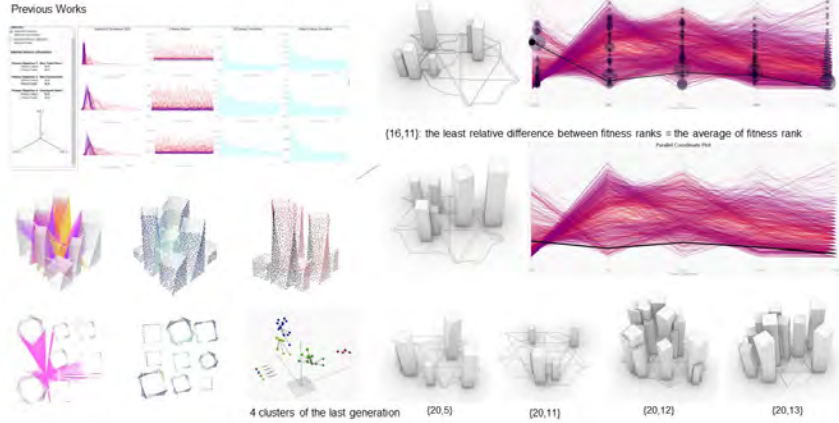
Evolutionary Processes in Design and the Impact of Multi-Objective
Evolutionary Algorithms Generating Urban Form



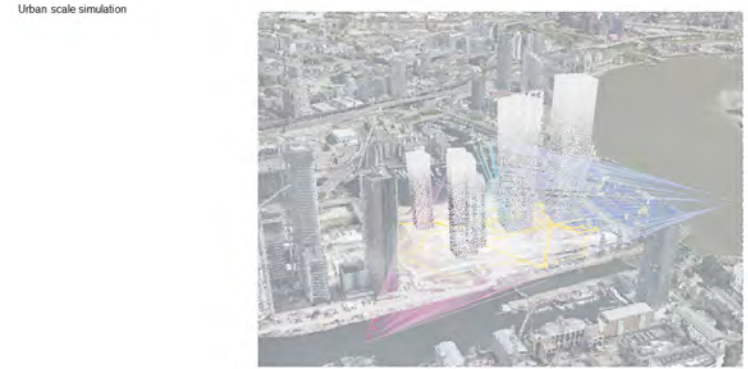
Visualization of the Design Problem

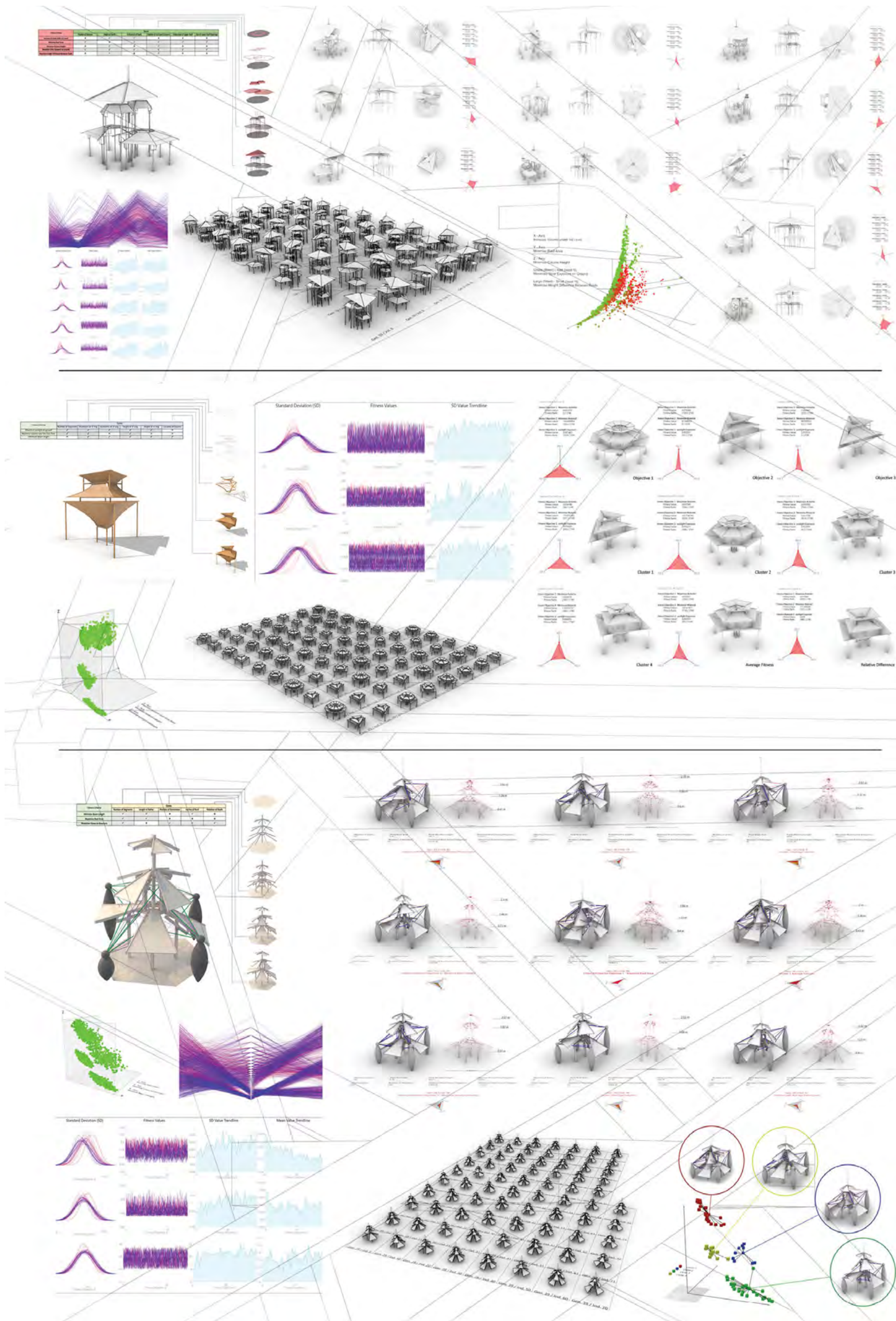


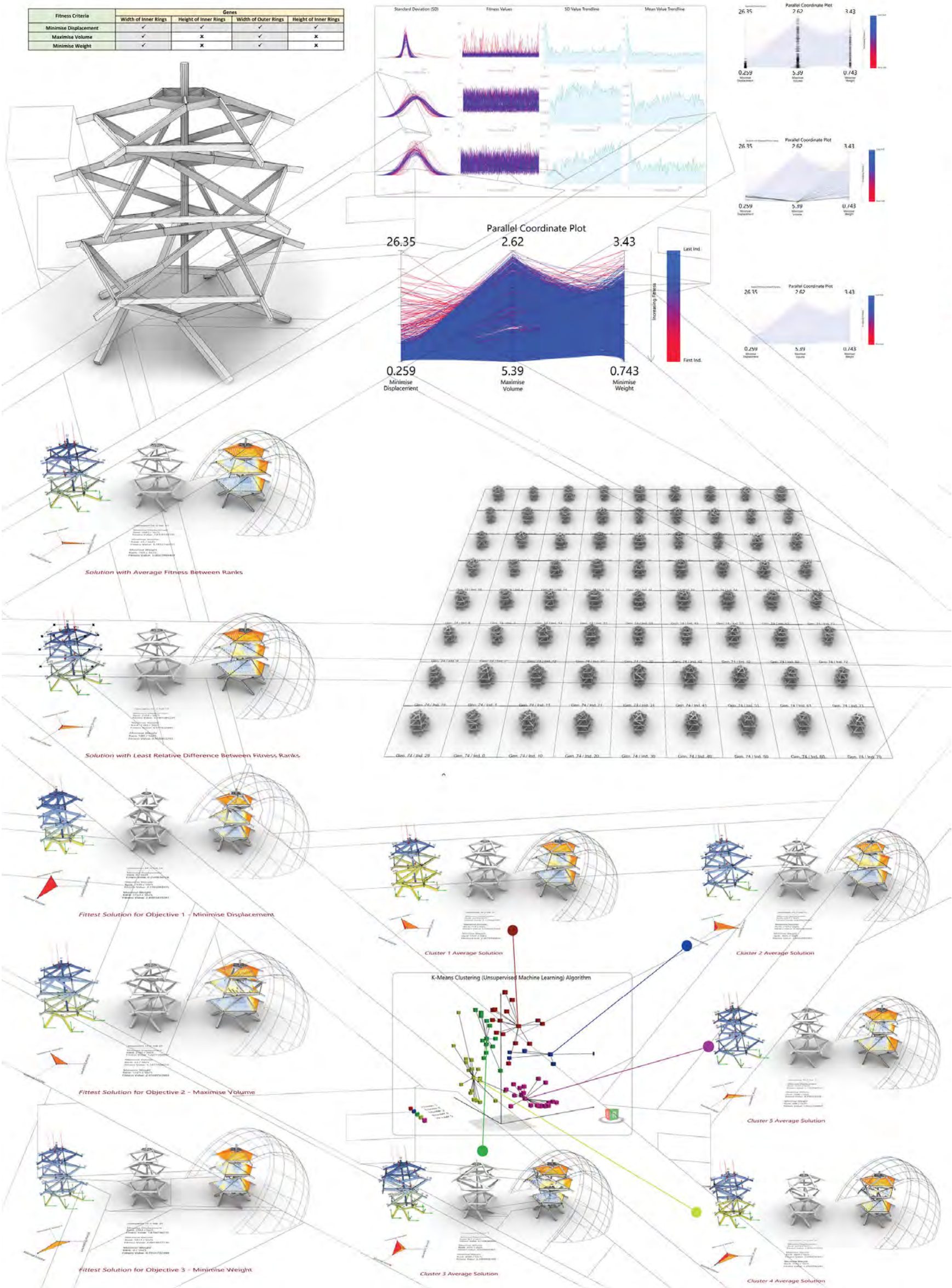
Solution Geometry



Rendering

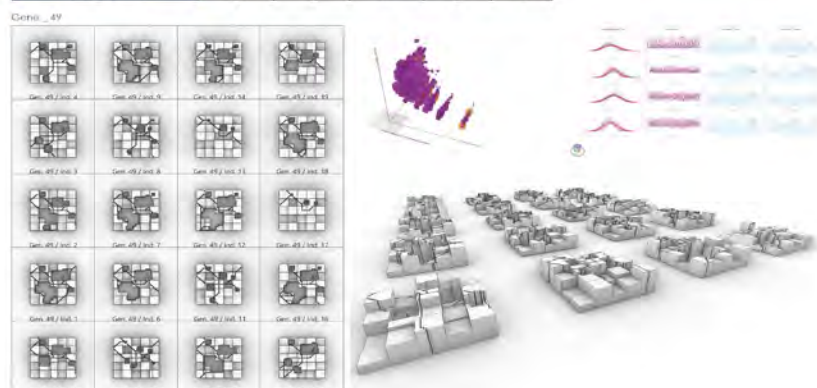




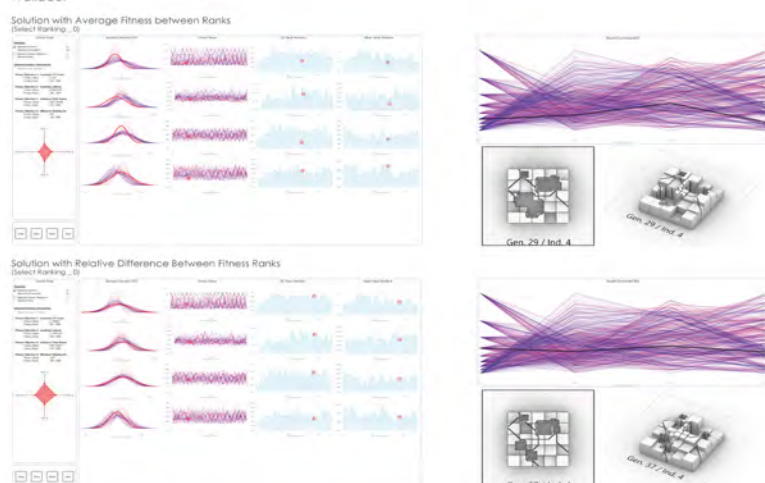


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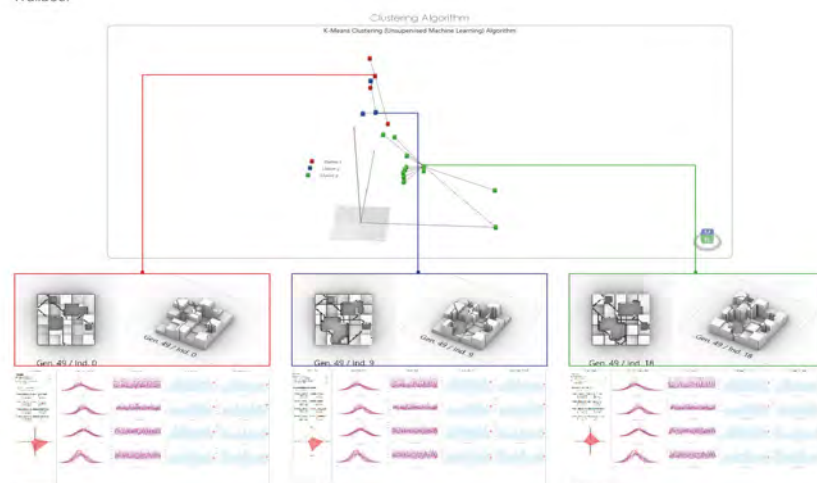
Fitness Criteria	Gender					
	Number of Courts	Courts per Location	Area of Courts	Courts per Location	Building Height	
Minimum Number of Courts	1	1	10	1	1	
Minimum Courts per Location	1	1	1	1	1	
Maximum Building Height	1	1	1	1	1	



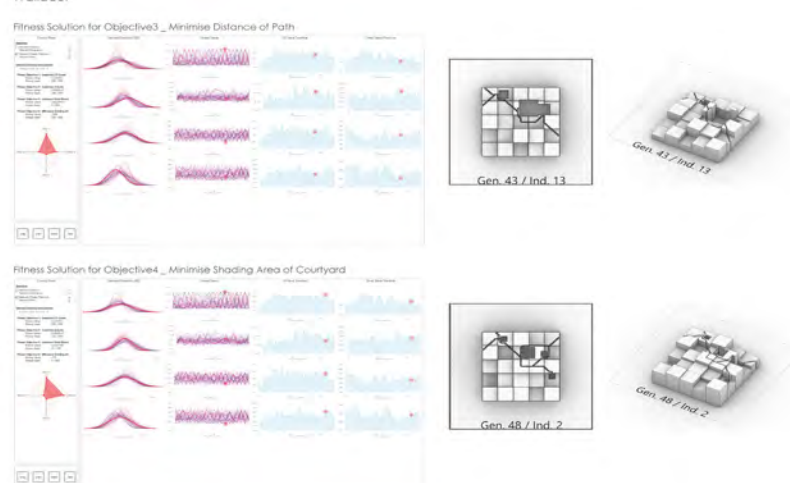
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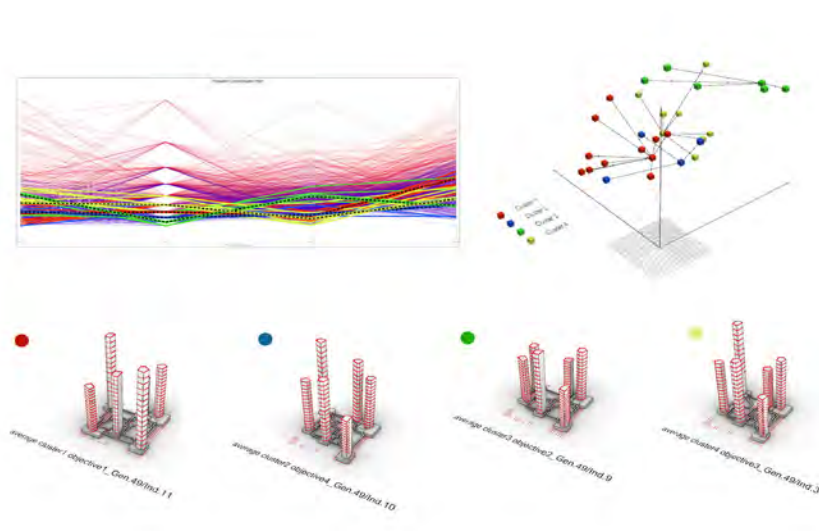
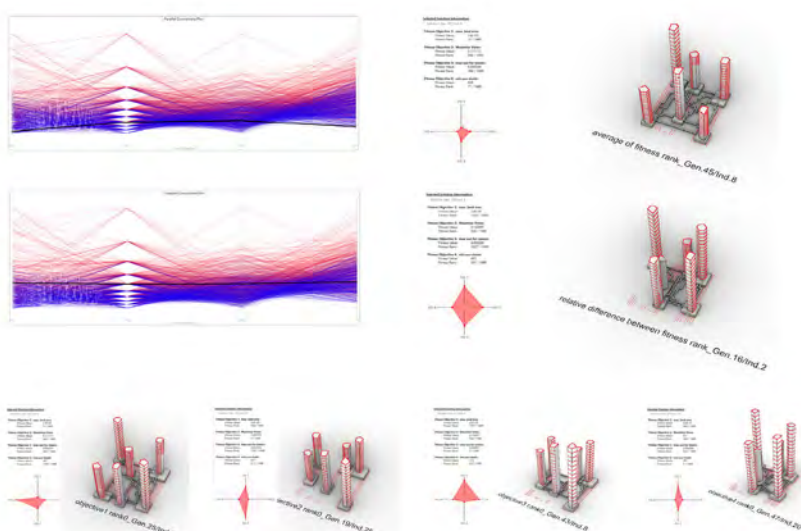
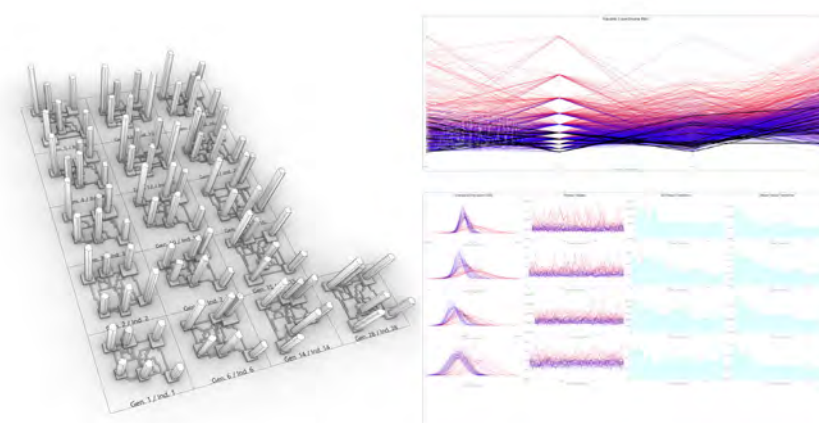


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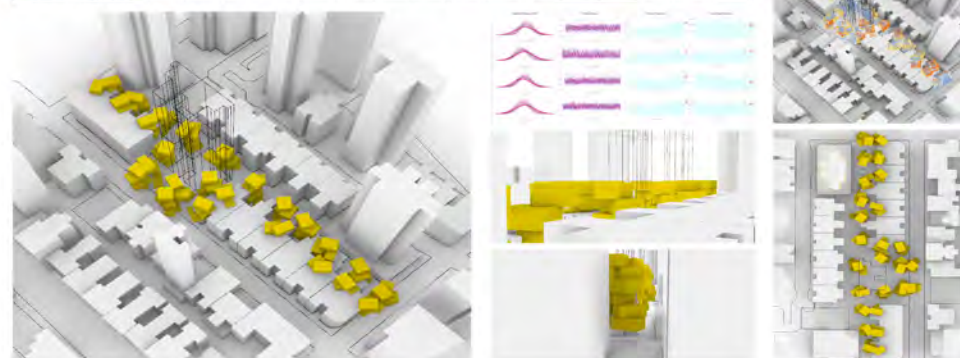
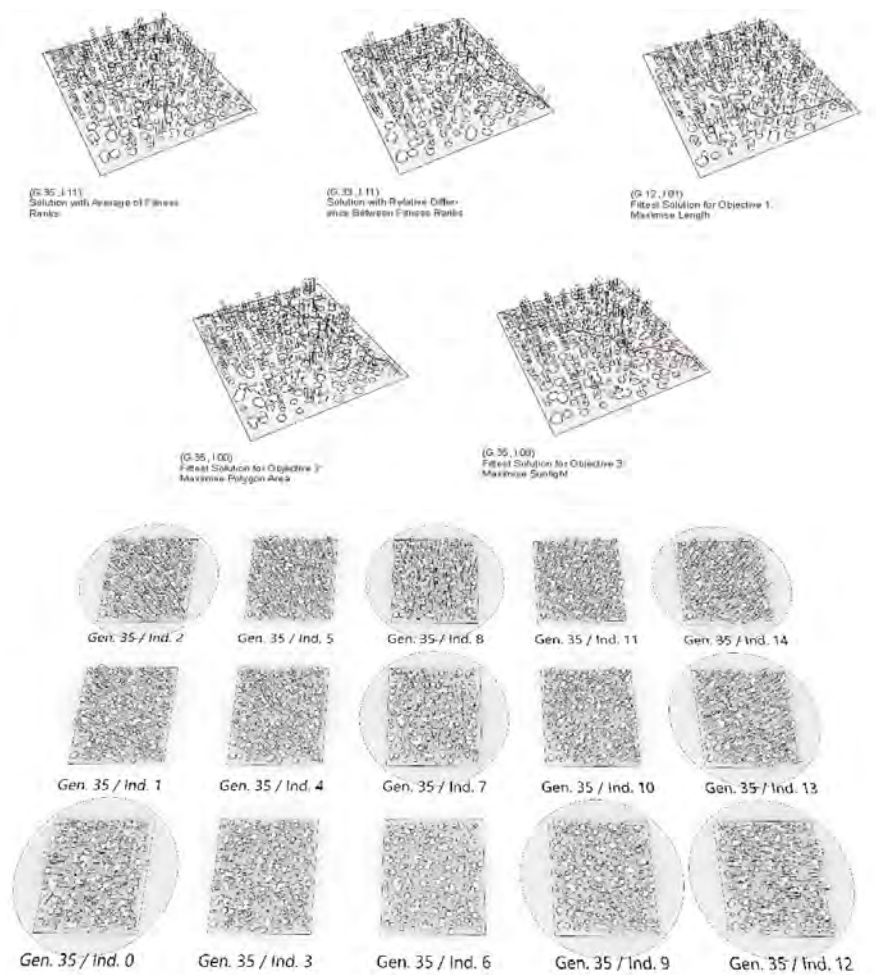
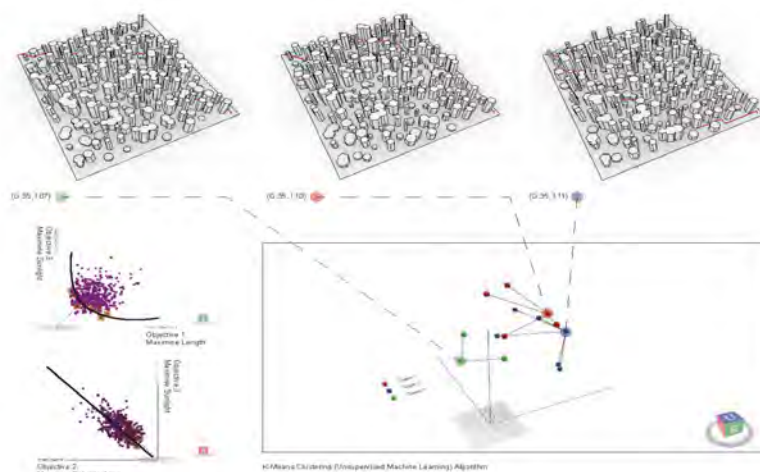


Fitness Criteria	Genes			
	Location of Podiums and Towers	Size of Podiums	Height of Towers	Shape of Towers
Maximized Land Area among Podiums	✓	X	X	X
Maximized View towards Harbour	✓	X	✓	✓
Maximized Solar Exposure of Towers		X	✓	✓
Maximized Solar Exposure of Ground Floor	✓		✓	✓

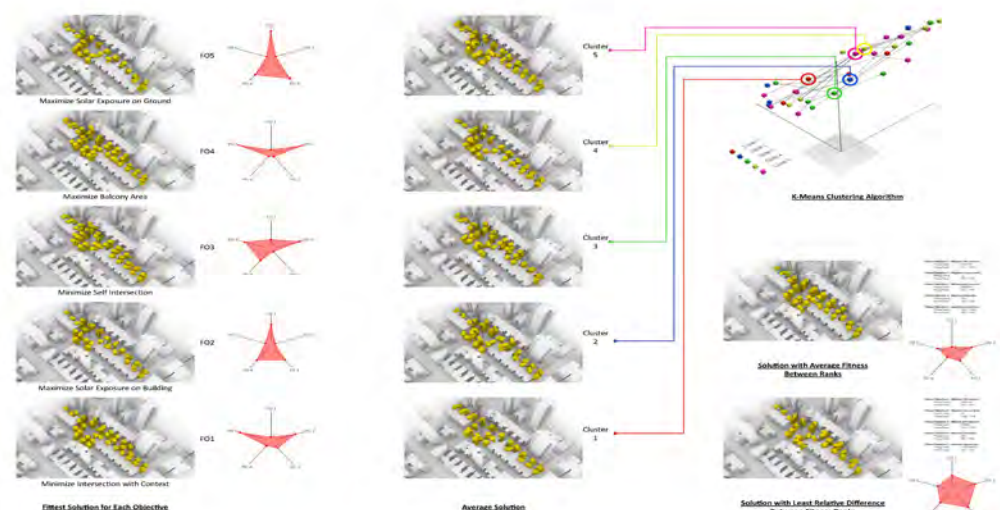
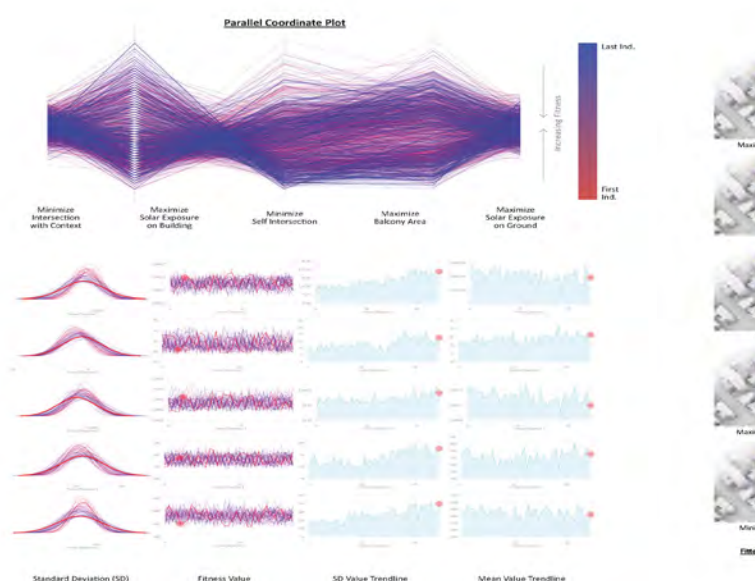
Phenotype: 6 petagon towers with a podium each AND an interconnected footbridge

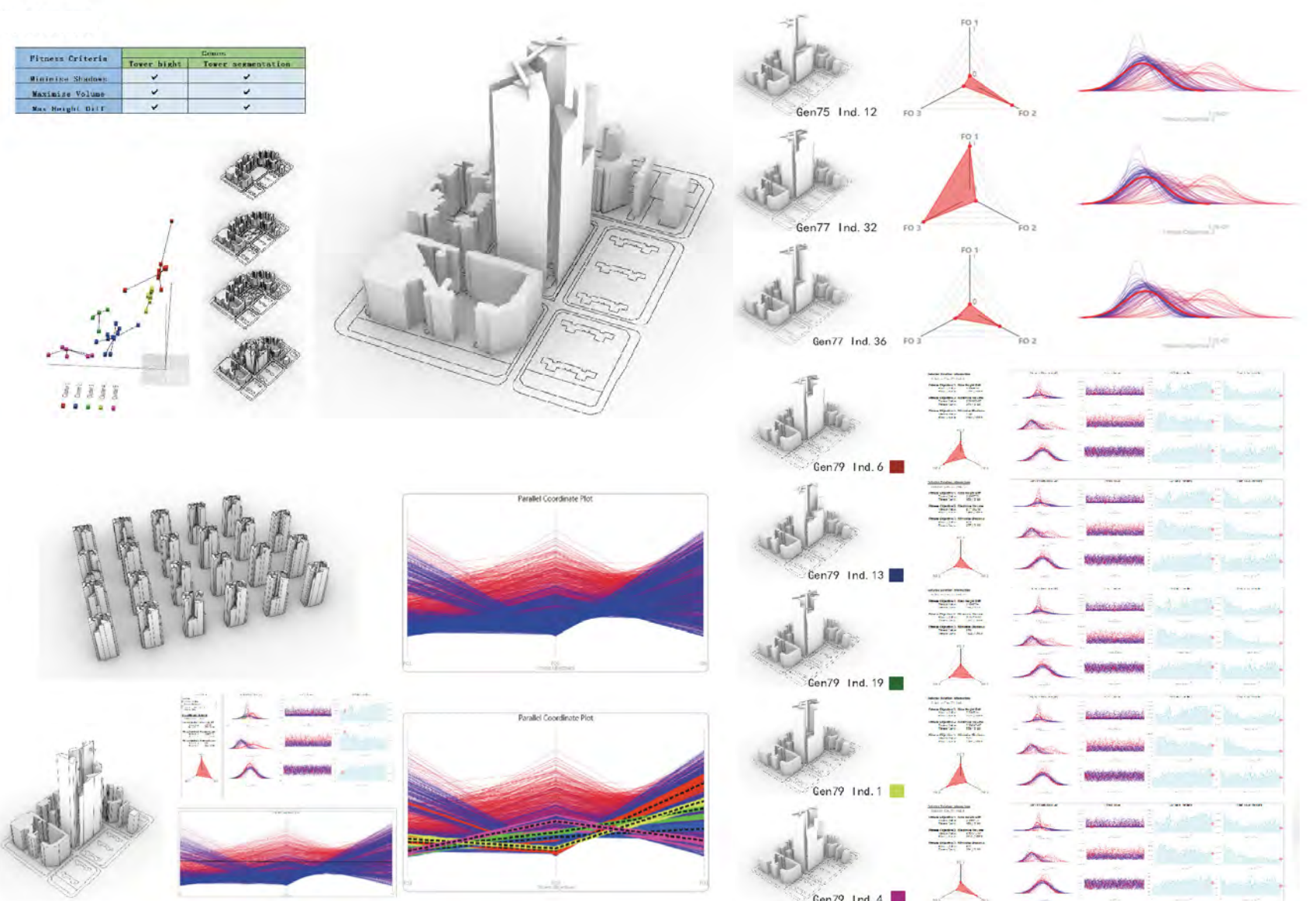
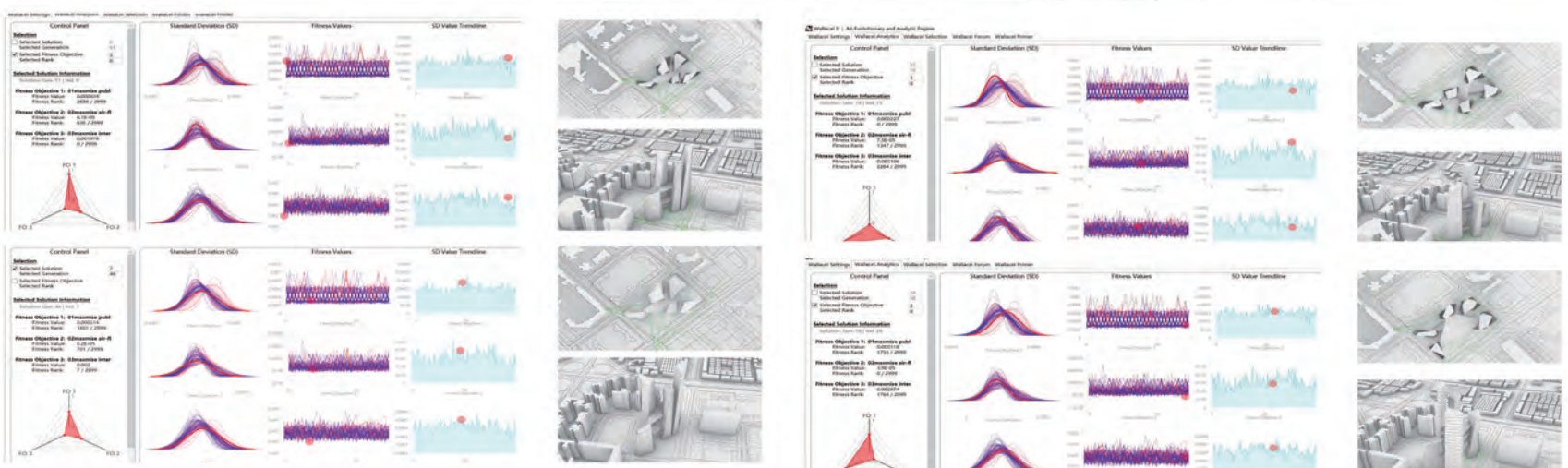
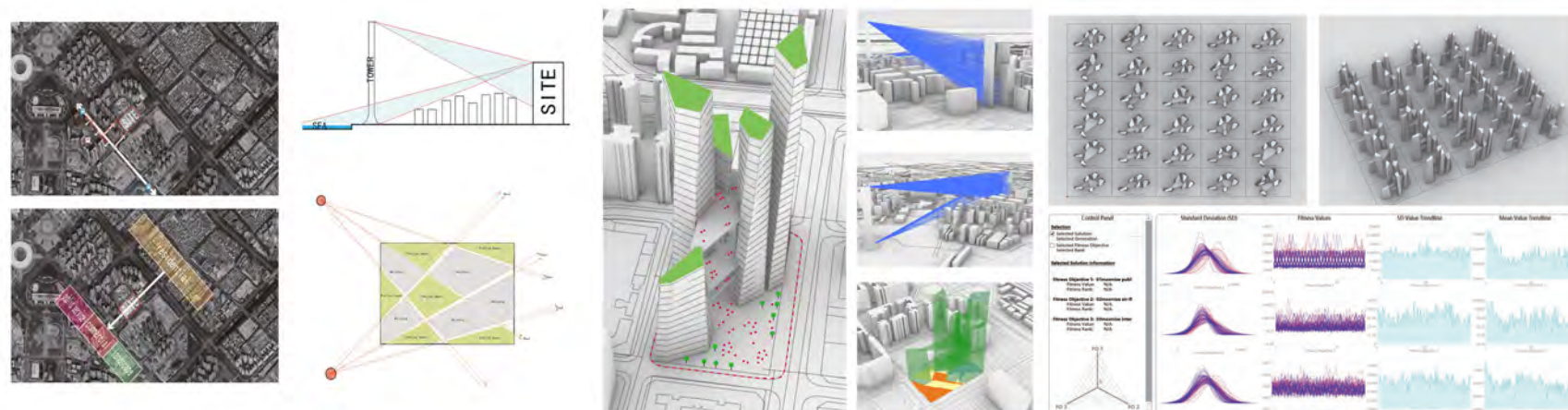


Evolutionary Processes in Design and the Impact of Multi-Objective Evolutionary Algorithms Generating Urban Form



Pareto Front Solution





Term	Definition
Convergence	When the fitness values of solutions evolved by the evolutionary simulation are very similar to one another (thus decreasing variation)
Crossover	Exchange of genes between two solutions (computation)
Crossover Rate	The number of genes exchanged between the two solutions (computation)
Design Problem	The method by which the design is expressed through 'objectives', 'bodyplan' and 'genes'
Divergence	When the fitness values of solutions evolved by the evolutionary simulation are distant from one another (thus increasing variation)
Elite / Archive	The fittest solutions in all preceding generations that are preserved in order to compete with the fittest solutions in the latest generation
Evo-Devo	Evolutionary Development - A subfield of evolutionary biology that examines the role of developmental biology in the evolutionary process
Evolved City	A city that has developed through a process of self-organisation and emergence, leading to complex systems that are informed by environmental conditions
Fitness Criteria / Fitness Objectives	The design objectives that will run the simulation, and to which the phenotypes will be evaluated
Fitness Landscape	The distribution of solutions of the search space in relation to one another and the relative complexity of the evolutionary simulation from navigating the solutions towards finding the fittest solution set
Fitness Rank	The ranking of each solution within the population according to its fitness value
Fitness Value	The empirical performance measure attributed to each solution according to the evaluation results
Gene	A single parameter that defines one part of an individual. In Grasshopper3D, this parameter is represented by a numeric slider (computation)
Gene Pool	The unique genes used by the different solutions in the population (computation)
Generation	A single iteration of the evolutionary algorithm (computation)
Generation Count	Number of generations (iterations) to be run by the evolutionary simulation (computation)
Generation Size	Number of solutions within each generation (computation)

Term	Definition
Genotype	All the genes that define a single solution. The genotype may be considered as the solution's 'blueprint' or DNA
Homeobox	A region in the DNA that is conserved across species. Homeobox genes play a key role in allowing for genetic regulation within the genome.
Homologous Structures	Morphological features of different species that share the same modularity and relative location to one another
Hox Cluster	Genes that control and regulate which body part grows in which part of an organism's body
Individual / Solution	A unit generated by the evolutionary simulation, represented by a genotype and phenotype, that comprises the population
Modern Synthesis	The acceptance of 5 key Darwinian principles by the majority of evolutionary scientists in the 1940s
Mutation	A change in a gene (or group of genes) in a genotype (computation)
Mutation Probability	The probability of a gene to mutate. This determines how many genes in a solutions genotype will mutate (computation)
Mutation Rate	Once the mutated genes are selected, this determines the intensity of how much each gene mutates
Natural Selection	Organisms selected for survival according to their fitness to environmental conditions
Objective Space	The distribution of solutions selected by the evolutionary algorithm in relation to their fitness values
Optimisation	The increase in fitness of a solution or population towards a very fit (or at times the fittest) value
Pareto Front	The solutions that are non-dominated by another solution. i.e. a solution that cannot be improved without negatively affecting the rank of another solution.
Phenotype	The formal (or otherwise) representation of the solution. The phenotype is the manifestation of the genotype.
Phenotypic Plasticity	Impact of the environment on gene expression of the phenotype
Planned City	A city that has developed through a top-down approach, with the aim of developing a finite and complete urban form from the onset of the city's development
Population	All individuals generated by the evolutionary simulation across all generations (computation)
Populationist	Signifies the uniqueness between solutions within a given population

Term	Definition
Regulation	The control of which genes act on which body parts
Search Space	All the possible solutions that can be explored by the evolutionary algorithm
Simulation	A single algorithmic run of the solver from start to finish.
Standard Deviation	Measures the distribution of a set of values from the mean value
Superblock	A urban unit of measure that is larger than a block and smaller than a patch, allowing for formal relationships to emerge between multiple blocks within an urban patch
Typologist	Considers the average solution of a population as an adequate representative of all solutions in the population

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